

FAULT TOLERANT CONTROL OF WIND TURBINES

BY

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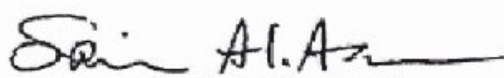
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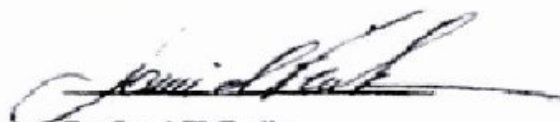
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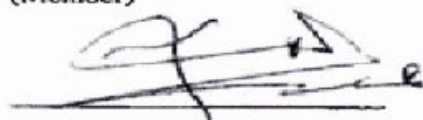
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Dedicated to My Parents, My Wife, My Son Hassan and
My Daughter Zainab

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LIST OF ABBREVIATIONS

AFTCS	:	Active Fault Tolerant Control Schemes
AFTC	:	Adaptive Fault Tolerant Controller
ANFIS	:	Adaptive-Neuro Fuzzy Inference System
AO	:	Adaptive Observer
BBO	:	Biogeography Based Optimization
CART	:	Controls Advanced Research Turbine
CPC	:	Collective Pitch Control
CSTR	:	Continuous Stirred Tank Reactor
CWIF	:	Caithness Windfarm Information Forum
DAC	:	Disturbance Accommodation Control
DFIG	:	Doubly Fed Induction Generator
DFT	:	Discrete Fourier Transform
ECG	:	Electrocardiography
EEWS	:	Estimation of Effective Wind Speed
EWS	:	Effective Wind Speed
FAST	:	Fatigue, Aerodynamics, Structures, and Turbulence
FDD	:	Fault Detection and Diagnostics
FDI	:	Fault Detection and Isolation or Identification
FE	:	Fault Estimation
FTC	:	Fault Tolerant Control
GA	:	Genetic Algorithm
GWEC	:	Global Wind Energy Council
HAWT	:	Horizontal Axis Wind Turbine
HSE	:	Health, Safety and Environment

ICA	:	Independent Component Analysis
IPC	:	Individual Pitch Control
LME	:	Linear Matrix Equality
LMI	:	Linear Matrix Inequality
LPV	:	Linear Parameter Varying
LQG	:	Linear Quadratic Gaussian
MCSA	:	Motor Current Signature Analysis
MLE	:	Maximum Likelihood Estimation
MPC	:	Model Predictive Control
MPPT	:	Maximum Power Point Tracking
NLGA	:	Nonlinear Geometric Approach
NN	:	Neural Network
NREL	:	National Renewable Energy Laboratory
PCA	:	Principle Component Analysis
PFTCS	:	Passive Fault Tolerant Control Schemes
PI	:	Proportional-Integral
PID	:	Proportional-Integral-Derivative
PIO	:	Proportional Integral Observer
PLS	:	Partial Least Squares
PMIO	:	Proportional Multiple Integral Observer
PSO	:	Particle Swarm Optimization
PWM	:	Pulse Width Modulation
QAT	:	Qualitative Trend Analysis
RBF	:	Radial Basis Function
RBF-NN	:	Radial Basis Function-Neural Network

RLS	:	Recursive Least Squares
RLS-FF	:	Recursive Least Squares-Forgetting Factor
RLS-KF	:	Recursive Least Squares-Kalman Filter
RLS-NG	:	Recursive Least Squares-Normalized Gradient
RMS	:	Root Mean Square
SDG	:	Signed Directed Graphs
SMC	:	Sliding Mode Control
SMO	:	Sliding Mode Observer
STFT	:	Short Term Fourier Transform
SVM	:	Support Vector Machine
T-S	:	Takagi-Sugeno
UIO	:	Unknown Input Observer
VAWT	:	Vertical Axis Wind Turbine
WT	:	Wind Turbine
WVD	:	Wigner-Ville Distribution
WWEA	:	World Wide Energy Association

ABSTRACT

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Wind energy is a promising renewable energy source. The idea of using fault tolerant system is that it could be used to maintain satisfactory operation even when faults occur. In this research, we study fault estimation and tolerant control based on a modeled wind turbine system. A full order unknown input observer is designed and studied to simultaneously estimate the states and faults during operation of wind turbine. Also, due to the nonlinearity in model that appears in the aerodynamic torque, different estimation techniques for aerodynamic torque is studied during partial load operation of wind turbine. Moreover, a comparative analysis between baseline controller and fault tolerant controller is studied under fault-free case and fault conditions. Results showed that recursive least squares estimation based on Kalman filter and recursive least square estimation based on normalized gradient outperformed recursive least squares estimation based on forgetting factor and Takagi-Sugeno based estimation. In addition, results showed that adaptive fault tolerant controller is capable to optimize the power efficiency during fault-free case and to accommodate the faults in the system while sustaining the power production of wind turbine.

ملخص الرسالة

الاسم الكامل: علي معتوق آل مسباح

عنوان الرسالة: التحكم المتحمل للخلل للتوربين الهوائي

التخصص: هندسة نظم و تحكم

تاريخ الدرجة العلمية: ديسمبر 2019

الطاقة الهوائية أحد أنواع الطاقة المتجددة الواعدة. فكرة استخدام التحكم المتحمل للخلل يمكن استخدامه للمحافظة على مستوى تشغيلي مقبول حتى عند حدوث الخلل. في هذا البحث، ندرس طرق التعرف على الخلل و التحكم لنظم التوربينات الهوائية. تم تصميم ودراسة مراقب مدخلات غير معرف من أجل تقدير حجم و قيمة للحالات والأعطال أثناء تشغيل التوربينات الهوائية. أيضًا ، نظرًا لعدم الخطية في النظام الذي يظهر في عزم الدوران الديناميكي الهوائي ، تتم دراسة تقنيات مختلفة لتقدير عزم الدوران الديناميكي الهوائي أثناء تشغيل الحمل الجزئي للتوربينات الهوائية. علاوة على ذلك ، تتم دراسة تحليلية للمقارنة بين وحدة التحكم الأساسية ووحدة التحكم المتحملة للخلل في حالة خالية من الأعطال وفي حالة وجود الأعطال. أظهرت النتائج أن تقدير المربعات الصغرى المرتكزة على عامل الترشيح Kalman والتقدير المربعي الصغرى المقدر بناءً على التدرج المعياري تفوق على تقدير المربعات الصغرى بناءً على عامل النسيان والتقدير القائم على Takagi-Sugeno. بالإضافة إلى ذلك ، أظهرت النتائج أن جهاز التحكم القابل للتكيف مع الأعطال قادر على تحسين كفاءة الطاقة خلال حالة خالية من الأعطال واستيعاب الأخطاء في النظام مع الحفاظ على إنتاج الطاقة من التوربين الهوائي.

CHAPTER 1

INTRODUCTION

1.1 Importance of Fault Detection and Diagnosis

There is an increasing demand on the safety, protection and reliability of many engineering and industrial systems such as chemical processes, manufacturing systems, power networks, wind energy conversion systems, aircrafts and electrical and mechanical machineries since they are all highly critical systems and directly impact the operation and maintenance of those systems. These mandates having technologies and controllers that can achieve safety, reliability and protection to personnel and equipment as well as minimizing costs and downtime.

However, standards process controllers are aimed to sustain acceptable operations by reimbursing several kinds of disturbances; yet, there are variations in the system that cannot be handled adequately. Those changes are called faults. A fault is defined as an unpermitted deviation of at least one characteristic property or variable of the system. Faults can be classified as plant faults, sensor faults and actuator faults. Examples of system faults are process parameter variations and component faults. Therefore, the faults must be detected, diagnosed and compensated for ensuring the system meets the required performance specifications. Modern facilities are highly complex with many numbers of variables which are monitored and controlled under closed loop scheme. Fault detection and diagnosis of abrupt and incipient faults for such plants can minimize downtime,

improve safety and reduce costs. In addition, it will assist operation and maintenance to make proper corrective actions to eliminate the abnormal behavior from the process [1], [2].

Process monitoring is one of the growing research areas in process control since there are new communication and instrumentations technologies that bring large amount of real time data. Process operators are eager to use this data to minimize plant downtime and optimize plant operations. Process monitoring actions involves fault detection, fault identification, fault diagnosis and process recovery for the plant. The terminology, in literature, related to fault diagnoses are not unique. However, process recovery is done by retuning the controllers, reconfiguring or repairing the process. During sensor faults, a fault reconstruction method can be implemented. So, process recovery is in fact dealing with fault tolerant control systems [1].

In industry, many examples can be found where insignificant faults have steered to a shutdown or equipment damage and resulted in expensive process interruption. Among the plentiful examples of deadly fault situations, two examples are presented. Chernobyl nuclear power plant in 1986 and Ariane 5 rocket in 1996, both of which experienced a massive explosion. Those catastrophic situations could have been avoided if fault diagnosis and tolerance technologies were implemented [3].

Aircraft was one of the first demanding application to have a fault diagnosis and tolerant operation against instability, suppression of flutter, actuators and sensors faults. This is not only limited to faulty components but also for any abrupt changes in the dynamical systems such as electrocardiography (ECG) analysis. This analysis identifies any abnormalities for heart performance which accounts for sudden changes in the dynamical systems out of their operating

limits. As a result, a fault tolerant system is not necessarily designed only for component faults but also for undesired dynamical changes.

1.2 Importance of Renewable Energy

One of the significant systems that shows promising results for renewable energy sources is wind energy conversion system. This system works by capturing the available wind energy and converting it to mechanical energy and then converting it into electrical power via generators or directly connecting it to a load like windmill and wind pump. In this research, wind turbine system is considered due to the high demand for clean energy sources and to minimize the dependency on fossil fuels as the major source of energy. Figure 1 shows the global cumulative of wind capacity installations form Global Wind Energy Council (GWEC) Global Wind Report 2017 which shows a positive trend in the demand for wind energy [4].

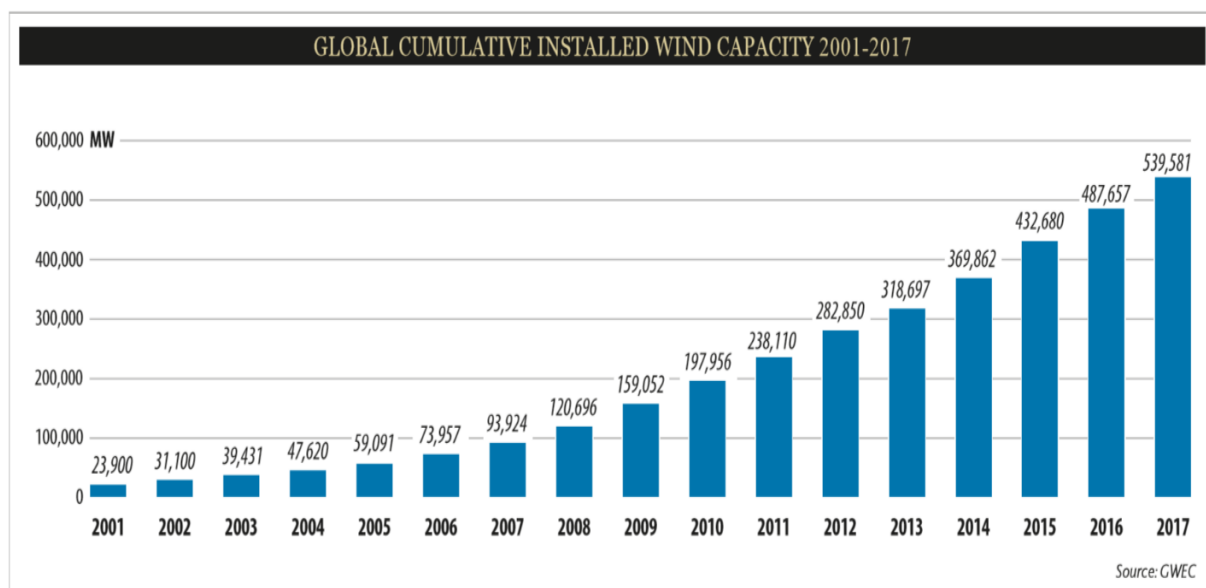


Figure 1: Global Cumulative Installed Wind Capacity 2001-2017 [4]

Also, some well-known US companies are purchasing renewable based power, so they are relying heavily on renewable energy sources such as solar and wind energy systems as shown in Figure 2.

It is clearly shown that wind energy accounts for the largest shares of renewable energy sources for the US companies and indicates that wind energy is considered as a very promising alternative energy source [5].

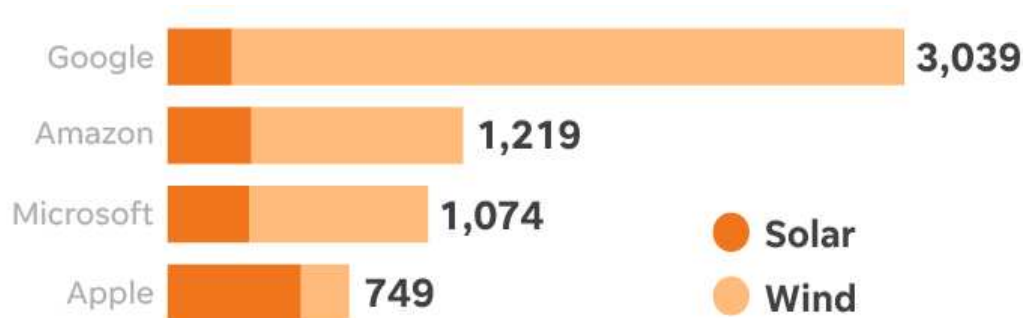


Figure 2: Top Global Corporate Buyers of Renewable Energy in Megawatts [5]

Moreover, as shown in Figure 3, statistics prove that there is demand increase and dependency on renewable energy sources compared with conventional types like coal and fossil fuels. The same figure shows the anticipated direction of global demand for the various types of energy sources and it shows that solar and wind energy have positioned themselves as promising and reliable sources of energy keeping in mind the continuous improvement in technology and efficiency enhancement in such systems [6].

Based on World Wind Energy Association (WWEA) report [4], by end of 2017, the overall installed capacity of wind turbines reached around 540 Gigawatt and the annual growth rate is around 10.8%. This installed capacity covers more than 5% of the world demand for electricity. Several countries are considering wind energy as a substitute energy source for fossil fuels and even nuclear energy. For example, 43% of power source for Denmark comes from wind energy. However, China is maintaining its position of the largest installed capacity for both solar and wind power. According to Global Wind Energy Council report in 2015, in European waters, average size of offshore wind turbine is around 4.2 MW and average distance from the shore area is around

43 km. Figure 4 shows different sizes of wind turbines for different manufacturers and illustrate the expected size in 2020 to reach around 20 MW.

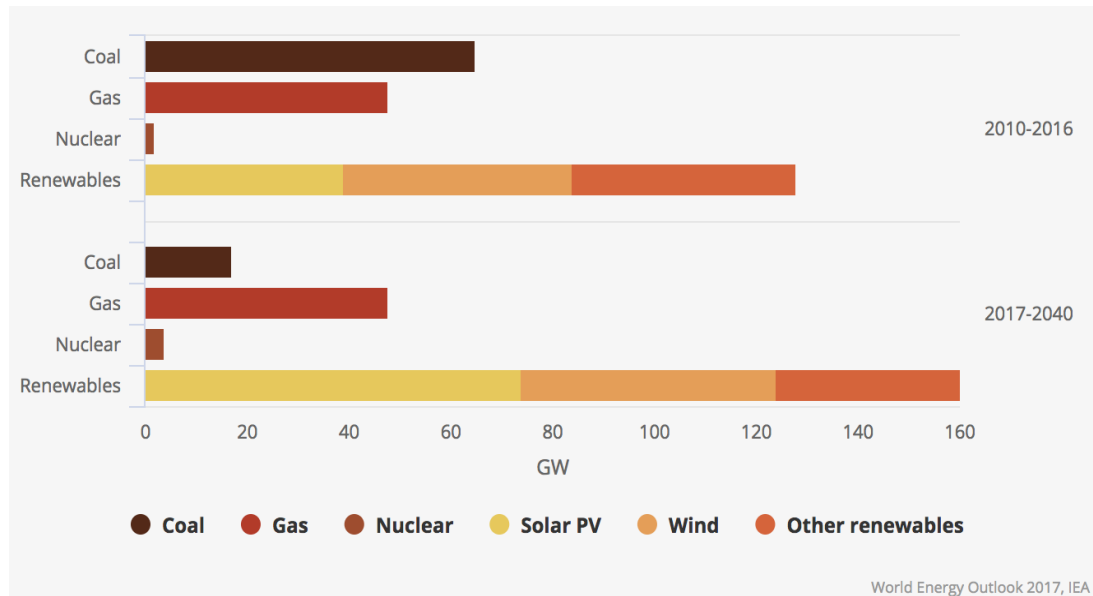


Figure 3: Global Average Annual Net Capacity Additions by Type [6]

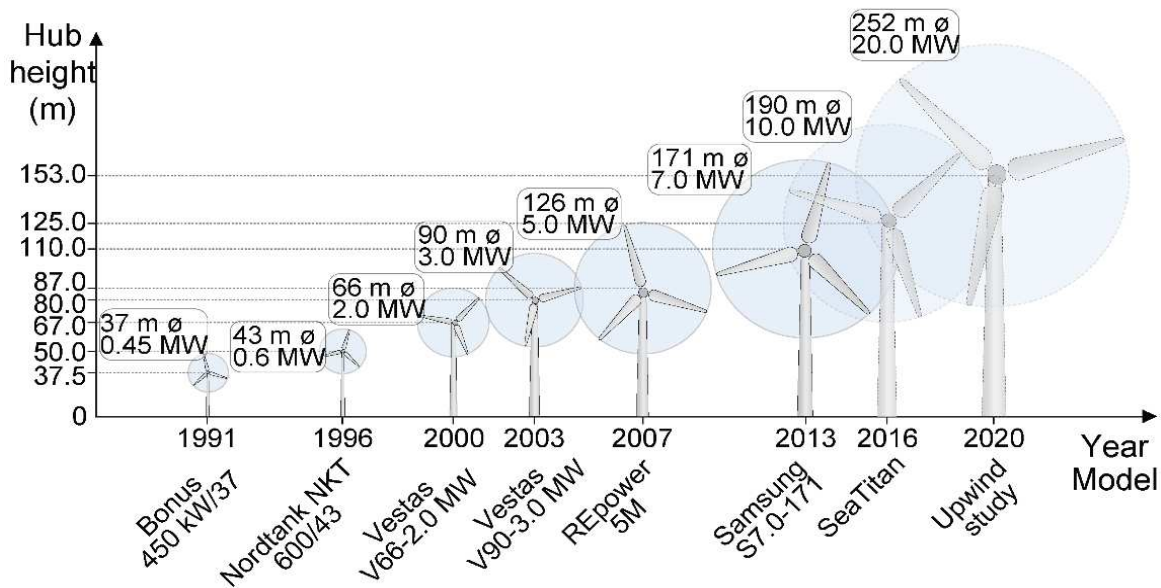


Figure 4: Different Wind Turbine Sizes with Different Manufacturers [6]

However, with that increase in demand for wind energy conversion system, two important factors must be seriously considered. First, the health, environment and safety (HSE) of people. Second,

the cost of operation and maintenance for wind energy conversion systems. Both require an intervention from technology advancement, namely effective fault diagnosis schemes and fault tolerant capabilities to reduce the impacts on HSE and costs. Table 1 shows replacement cost for 5 MW wind turbine. Such an example illustrates the considerable replacement cost.

Table 1: Replacement Cost for 5 MW Wind Turbine [7]

Part	Cost
Rotor	\$1.9-\$2.3 millions
Blade	\$391,000-\$547,000
Blade Bearing	\$625,000-\$872,000
Gearbox	\$628,000
Generator	\$314,000
Electronic Module	\$16,000

1.3 Significance of Fault Diagnosis and Control for Wind Turbines

What drives to have fault diagnosis and/or fault tolerant control capabilities is the number of accidents that happen in the wind turbine industry which affects human life, equipment and interruption in power production. Based on Caithness Windfarm Information Forum (CWIF), the number of accidents is increasing as more turbines are installed. The average accidents per year from 1999-2003 is 44, and from 2004-2008 is 94, and 196 accidents every year from 2014-2018. CWIF claims their data only represents a small percentage that captures the accidents that happened in wind farms and turbines and the evidence can be found in [5] . This article has reported around 737 accidents during 2016 from UK offshore wind farms most of which are during operation. Also, statistics showed that around 44% of the medical emergencies were related to wind turbine; however, comparing this data to CWIF data shows only 4 incidents were included

which accounts for only 0.5%. Despite the above comparison, CWIF data still provides an excellent statistic of the accidents occur since it shows the type of accidents and their consequences. However, the data before year 1997 was related only to fatal incidents as shown in Figure 5.

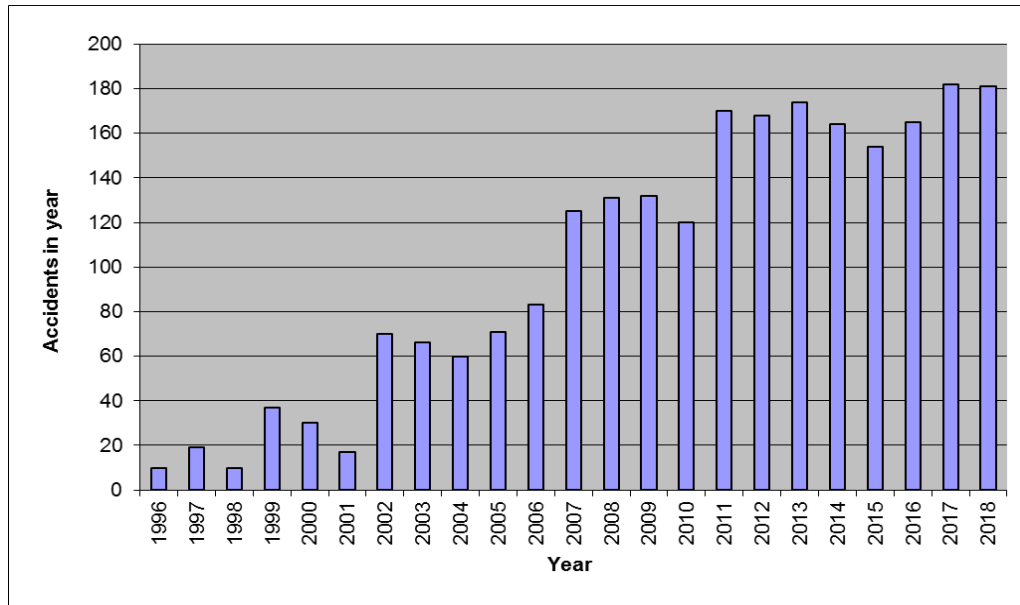


Figure 5: Accumulative Accidents Every Year in Wind Turbines from CWIF 2018 Data [8]

Therefore, having a reliable and fault tolerant capability for wind energy conversion system (WECS) is significant especially for wind turbine installed at remote areas such as offshore wind turbines since maintenance for such cases are not easy to be handled within short period of time due to commuting distance and accessibility. Figure 6 shows statistics resulted from two large surveys on European wind turbines from year 1993 to 2006 [9]. First, Wissenschaftliches Mess- und Evaluierungsprogramm (WMEP) which has covered 1500 onshore wind turbines with 190,000 monthly reports and 64,000 incident reports by using manual documentation with logbook for each wind turbine from 1989 to 2006. Second, Landwirtschaftskammer Schleswig-Holstein (LWK) which covered more than 650 wind turbines from 1993 to 2006. Those surveys illustrate

the type of faults in wind turbine with frequency of occurrence as well as the downtime repair for each fault. Figure 6 illustrates the highest failure rate occurs in electrical systems. Also, the longest downtime per failure was due to gearboxes failures which are basically related to the drive train subsystem. Moreover, 25% of faults in the wind turbine system caused around 95% of downtime and 75% of faults caused only around 5% of downtime.

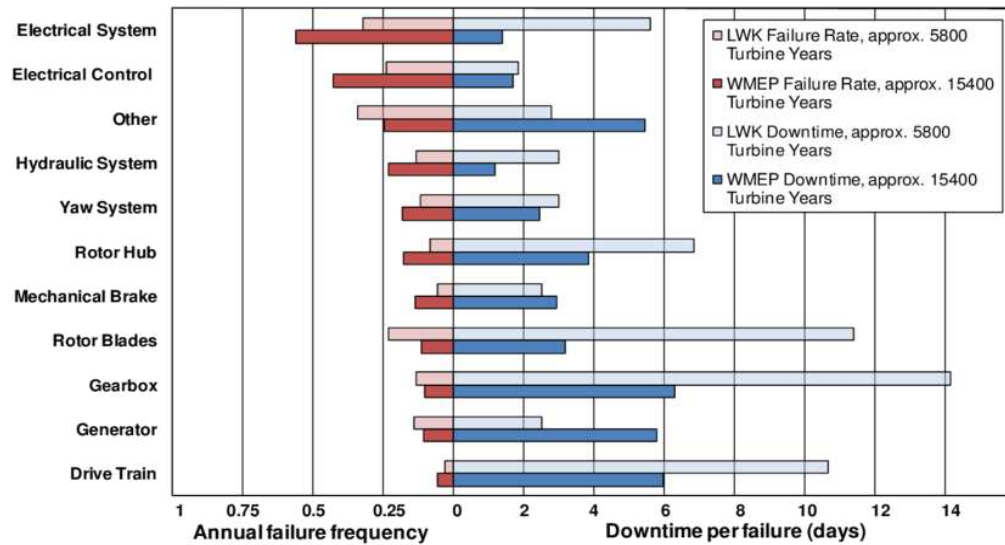


Figure 6: European Wind Turbine Failure Statistics from 1993 to 2006 [9]

In addition, for offshore wind turbines, the maintenance work activities are difficult due to several reasons such as commuting distance, mean of transportation and weather conditions. Figures 7 and 8 show maintenance crew doing the required maintenance on an offshore wind turbine.

Consequently, from the presented previous statistics, studies and data, it is of paramount importance to have highly reliable wind turbine control systems to avoid health, safety and environment concerns as well as operation and maintenance costs. This is very important in order to coop with the high demand of energy and specifically on wind energy sector.



Figure 7: Maintenance Crew Arriving at Offshore Wind Turbine [10]

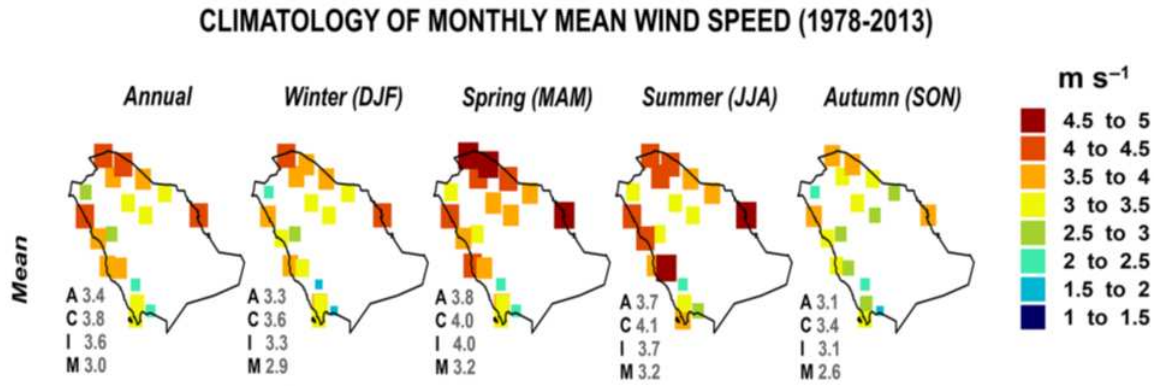


Figure 8: Maintenance Crew on Offshore Wind Turbine [10]

1.4 Saudi Arabia Wind Farm Project

Saudi Arabia received different bids from four companies challenging to build a \$500 million Saudi wind farm project with a capacity of 400 MW produced by 99 wind turbine units. Dumat Al Jandal wind project deal is won by a group led by EDF Energies Nouvelles and Abu Dhabi Future Energy. This project is expected to start production in early 2022. The location was selected based on studies that showed the availability and capability of wind. A previous study was done supporting this proposed location in Saudi Arabia as shown in Figure 9.

The average annual generation from the wind plant is expected to be around 1.4 TWh. And it is considered as the first wind utility scale system in Jouf province which can power up to 70,000 houses. With this project, it is expected that carbone dioxide emmisions will be reduced annually by more than 900,000 tons.



(A) All series; (C) coast series; (I) inland series; (M) mountain series.

Figure 9: Monthly Mean Wind Speed in Saudi Arabia [105]

It is worth to mention that Saudi Aramco installed one wind turbine in the same place in 2017. Moreover, Saudi Arabia has 12 more renewable initiative projects to minimize the usage of fossil fuels and maximize clean energy sources.

1.5 Problem Statement

To have a reliable source of energy with minimum maintenance costs and safe operation, a fault tolerant capability of wind turbine system is needed. This is achieved by having system model with adequate accuracy especially for model-based techniques. Also, robust fault estimation algorithms are implemented and enhanced using heuristic algorithms to accommodate both actuator and sensor faults and compensate them to maintain stability and operation of the overall system.

1.6 Thesis Objective

1. Studying the Takagi-Sugeno (T-S) fuzzy modeling approach.
2. Studying the robust observer-based estimation using of simultaneous actuator and sensor faults under disturbances.
3. Studying different techniques of aerodynamic torque estimation due to its nonlinearity.
4. Studying an adaptive fault tolerant control scheme to accommodate faults during partial load operation.

1.7 Thesis Organization

This thesis is organized as follows. Chapter 2 presents the fault diagnosis and tolerant control approaches implemented in academia and industry and an introduction about T-S fuzzy modeling. Chapter 3 presents the wind turbine system description and modeling including control concept and fault scenarios and conditions. Chapter 4 presents the proposed methodology using optimized T-S fuzzy modeling and using robust fault estimation algorithm and optimizing its parameters using heuristic algorithms. Chapter 5 presents the simulation results and summary and conclusion are presented in Chapter 6.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

Due to the benefits and positive outcomes of having fault tolerant capabilities as mentioned in previous sections, many researches were conducted in such fields in many engineering applications with established benchmark models such as motors, robotics, quadrotors, aircrafts, wind turbines and so on. The below literature is focusing on general application for different fault tolerant and diagnosis control techniques. Next, fault estimation and fault tolerant control (FE/FTC) schemes are presented specifically in wind turbine systems with more attention on T-S based modeling approach for its great advantage in approximating highly nonlinear systems and for its smoothness properties.

2.2 Fault Diagnosis Approach

Gao et al, [2] and [18], presented a two-part survey for fault diagnosis and fault tolerant techniques developed in the literature in 2015 in which authors have categorized the techniques into model based, signal based, knowledge based and active based fault diagnosis approaches. The work on fault diagnosis goes back to the last four decades but the mentioned surveys focused more on the outcomes published in the last decade.

2.2.1 Model-Based Techniques

In [2], for deterministic model-based approaches, there were several techniques implemented in literature for different engineering applications. Eigenstructure assignment, linear matrix inequality (LMI), unknown input observer (UIO), parity relation, stability factorization for frequency domain and some other advanced observer-based techniques such as adaptive observer (AO), proportional and integral observer (PIO), proportional multiple integral observer (PMIO), and sliding mode observer (SMO). Those advanced observers are based on creating an augmented system that combines both the faults and system states in order to simultaneously estimate both fault and system states.

Also, combined techniques of advanced observers were reported in the literature to enhance and achieve certain objectives, for example, in altitude satellite system and in gas turbine engine. For stochastic model-based approaches, there are also various techniques implemented in literature such as Kalman based filters and their modified versions to handle several challenges. Other techniques include generalized likelihood, cumulative sum algorithms, parameter estimation based on system identification concepts. Also, other stochastic based techniques were reported for Markovian jumps and Brownian motion systems.

2.2.2 Signal-Based Techniques

The second approach for fault diagnosis is signal-based method which is not based explicitly on input-output models but rather uses the measured signal for real time monitoring and diagnosis which have been implemented in several engineering applications. This method is classified into three classes: time-domain, frequency-domain and time-frequency domain-based techniques [2].

For time domain-based signal fault diagnosis technique, it is based on extracting the time domain features to detect the faults such as the RMS change in the current for power converters, the slope of induction current over time, motor phase currents and covariance for sensor measurement for aircraft. Also, this technique can be applied in a two-dimensional data where vibration signal is converted to image and by utilizing different transforms one can have pattern classification and image texture analysis.

For frequency domain-based signal fault diagnosis, it is based on extracting the frequency domain features of the measured signals using spectrum analysis such as discrete Fourier transform (DFT) and motor current signature analysis (MCSA) for motor faults as well as acoustic fault detection for gearboxes.

For time-frequency based signal fault diagnosis, it is suitable for transient and dynamic based nature signals since they have time varying frequency spectrum. Those techniques include, but not limited to, wavelet transform (WT), Wigner-Ville distribution (WVD), short term Fourier transform (STFT) and Hilbert-Huang transform which all have been widely used in motor and machinery fault diagnoses.

2.2.3 Knowledge-Based Techniques

In [18] presented the second survey paper covering the knowledge based and active based fault diagnosis approaches. For knowledge-based methods, a large amount of historical data is required upon which artificial intelligence techniques are applied and that is why it is also called data driven based approach. However, the knowledge-based approach is classified into qualitative and quantitative based techniques.

For qualitative based techniques, there is expert system-based method which relies on a set rules that are derived from human experience. Also, there is qualitative trend analysis (QTA) and signed directed graphs (SDGs).

For quantitative based techniques, it is classified into statistical analysis and non-statistical analysis-based methods. For statistical analysis-based methods, there are several techniques such as principle component analysis (PCA) applied in diesel engines, CSTR, and rolling bearing; support vector machine (SVM) applied in wide application such as power transformer and machinery fault detection; partial least square (PLS) and independent component analysis (ICA) which are also used in the biological processes and other applications as well. For non-statistical analysis-based methods, which are good in adaptive learning and nonlinear approximation, there are several techniques such as neural network (NN) and fuzzy logic. For neural network, there are so many methods that have been done such as radial basis network, self-organizing maps, and recurrent dynamic networks and so on.

2.2.4 Active Fault Diagnosis Based Techniques

In [18], active fault diagnoses approach is based on injecting a designed input signal to the process for a short interval to test the faulty modes of the system which was applied in PWM converter and battery system. In general, Fault detection and diagnosis schemes rely on the redundancy concept which is either based on hardware redundancy or software (analytical) redundancy.

However, in this context, the major focus is on the analytical redundancy since it became the main area of research since 1980's with the development of control theory. The coming literature review is focused on model-based fault diagnosis approach for wind turbine system.

2.3 Fault Tolerant Control Techniques

The fault tolerant control systems can be defined as such systems that can automatically maintain overall stability and satisfactory performance in event of faults and malfunctions in the plant. There are two major categories of fault tolerant control systems: passive fault tolerant control schemes (PFTCS) and active fault tolerant control schemes (AFTCS).

However, those different fault tolerant techniques were implemented in many engineering applications other than wind turbine such as truck-trailer [19] and [20]; quadrotors [21], [22], [23] and [24]; robotics [25], [26], [27] and [28]; tank systems [29], [30], [31] and [32].

2.3.1 Passive Fault Tolerant Control Schemes

PFTCS primarily focuses on building robust control systems but with a fixed structure/parameter controller that would handle a set of limited faults. However, it is getting much attention in literature since it neither requires fault diagnosis schemes nor reconfiguration of controller parameters and it is practically with less computational burden and implemented in literature for wind turbine applications such as [33], [34], [35] and [36].

2.3.2 Active Fault Tolerant Control Schemes

Unlike PFTCS, AFTCS applies online fault diagnosis schemes and adaptive in terms of reconfiguring the controller parameters and/or structure of actuators and sensors which is solely based on the measurement or estimates of the unknown plant. AFTCS is further

subdivided into online redesign methods and projection-based methods. Online redesign methods determine the controller parameters online according to the changes and faults occurring in the system. However, the projection-based methods are based on the selection among offline pre-designed controllers depending on the fault conditions [37]. AFTCS is implemented in literature for wind turbine applications such as [38], [39], [40], [41] and [42].

2.4 Model Based Fault Diagnosis and Control Techniques for Wind Turbine

In this context, the focus of research is on model based techniques and detailed literature review is presented with more attention on T-S observer model-based techniques. Both FTC schemes AFTC and PTFC implemented on two widely used wind turbine benchmark models.

In [43], the authors proposed a T-S fuzzy modeling of the nonlinear system and unknown input fuzzy (UIO) is considered to decouple unknown inputs and estimate the augmented states. Moreover, linear matrix inequality (LMI) is utilized to ensure stability of error convergence and dynamics. Finally, a signal compensation technique is implemented to remove the effects from simultaneous actuator and sensor faults and ensure stable dynamics. A pre-existing controller was assumed as nonlinear feedback controller and designed in a fault free scenario. However, there are some limitations in this work. First, no details about the structure and approach for the pre-existing controller design. Second, no time delays were assumed in this work. Third, no switching mechanism was stated when there is sensor failure because redundancy was assumed. Forth, it considered only one sensor fault and actuator fault in the converter. Fifth, parameter uncertainties were not considered. However, the developed work in this paper was implemented on a well-known benchmark model of 4.8 MW wind turbine. The main role of this paper was robust fault estimation using UIO and fault compensation of T-S fuzzy model composed of 24 local models

and subjected to simultaneous actuator and sensor faults (incipient or abrupt) while considering partially decoupled unknown disturbances and the upper bound of those unknown inputs was not required. Also, modeling errors were compensated by adding error components in the model structure and resulted in a very good approximate of the nonlinear model. As a future work recommended by the author was to consider stochastic nonlinear system subjects to Brownian motions.

In [44], pitch actuator system was considered for wind turbine system and designed a modified SMC based controller to accommodate actuator and sensor faults. The main contribution of this paper is combining proportional-proportional-integral observer (PPIO) and sliding mode control (SMC) to have accurate blade pitch reference tracking despite of actuator and sensor faults. Also, integral sliding surface based on sliding mode control (ISMC) was developed to stabilize error dynamics during sliding motion and to be robust against mismatched and matched uncertainty. Stability analysis was proved using LMI and Lyapunov theory. Moreover, the sliding surface design used. LMI was used to attenuate the effect of disturbances on fault estimation signal by L_2 norm minimization. Despite that sensor fault showed a direct impact on the sliding variable which in turns lead to incorrect measurement, it was shown that combination of SMC and PPIO works well for actuator and sensor faults that occur simultaneously.

In [33], a fault tolerant control (FTC) approach was implemented to achieve power maximization by capturing wind energy during operating at low wind speed. Also, T-S fuzzy based modeling was utilized with effective wind speed (EWS) estimation by robust estimation of unknown aerodynamic torque. However, T-S fuzzy model was represented only with two local models. The sensor fault and state estimation including EWS was achieved by using proportional multiple integral observer (PMIO). EWS estimation was based on aerodynamic torque inversion and FTC

was based on T-S fuzzy linear output feedback controller to achieve the tracking of optimal rotor speed. Stability of the controller was proved with H_∞ performance constraints and formulated via LMI. The implemented approach maintained the same controller, under faulty and fault-free cases, to compensate for the impacts originating from faults by using the linear PMIO. However, the pitch subsystem model was not considered since the pitch angle is kept at its optimal value at zero during low wind speed operation. Also, the author considered only constant additive sensor faults in the drive train subsystem without actuator faults. In addition, it was assumed that the q^{th} derivative of the augmented signal is bounded. Moreover, the use of single PMIO estimator for sensor fault and aerodynamic torque would results in spikes in the aerodynamic torque estimate and hence in the effective wind speed estimation especially when fault occurs abruptly.

In [45], an LMI based robust multi objective collective pitch controller (CPC) was implemented in National Renewable Energy Laboratory (NREL) 5 MW benchmark wind turbine model for generator speed regulation during high rated wind speed. The LMI provided the advantage of adding multiple constraints namely H_2 for control action optimization with performance, H_∞ for efficient disturbance rejection and $\mathcal{H}_2/\mathcal{H}_\infty$ tradeoff between the two as well as pole clustering to improve transient response. To tackle the uncertainty in the system, a polytopic model was utilized at different operating points. Also, individual pitch controller (IPC) was combined with CPC to reduce mechanical fatigue load which is mostly needed in large wind turbine systems. The comparison between conventional PI controller and LMI based controller shows that the latter has better performance and reduced the cyclic fatigue loads but exerted more control effort to mitigate the loads significantly which would increase the life time of wind turbine by ensuring that it is working on the designed operating parameters. Also, the proposed controller showed better performance in terms of full load power and speed regulation.

In [46], a hybrid technique based on a combination of eigenstructure assignment and genetic algorithm optimization for augmented observer was implemented for robust fault estimation of wind turbine system to attenuate the uncertainty caused by process disturbances and fault estimation errors under sensor and actuator faults without process faults. Both incipient and abrupt type of faults were considered. However, modeling errors were not addressed and need to implement the proposed method with real industrial data.

In [47], as in [45], the authors proposed a collective pitch controller on NREL5 MW offshore wind turbine FAST model but with fuzzy predictive controller. Also, the wind turbine model was different than in [45] by implementing T-S fuzzy model. Moreover, the number of fuzzy rules was minimized based on certain criteria of gap metrics. The proposed controller is based on model predictive control coupled with gain scheduled PI controller. A Kalman observer was designed for the unmeasurable states which contains two design parameters in covariance of two stochastic signals which gives a needed method to design those parameters. A comparison study was done between the proposed algorithm with gain scheduled PI controller and a mixed $\mathcal{H}_2/\mathcal{H}_\infty$ controller. This study focuses on region 3 of wind turbine operation mode in which wind speed lies between the rated speed up to cut out speed. In this region, the objectives are to obtain rated power, mitigate the mechanical loads and regulate at rated speed. Also, it was focused on designing pitch controller while considering the constraints in the pitch angle namely the rates of change in the pitch angle and its limits. No wind speed estimation was implemented assuming that fuzzy model approach designed would accommodate the imprecise measurement of wind speed. The IPC based PI controller was designed to decrease the turbine blade moment and MPC used to control pitch angle to maintain power and generator speed and at desired values. Both gap metric and Kalman filter have design parameters that needs optimal selection which is a gap in the

proposed work. However, simulation of the proposed algorithm with baseline controller (gain scheduled PI controller) and mixed H_2/H_∞ controller proved that the proposed one outperformed the other two approaches.

In [34], the authors developed adaptive estimation algorithm to estimate actuator fault and states simultaneously and robust controller based predictive FTC compensation strategy on discrete time linear 4.8 MW wind turbine benchmark model. The proposed predictive FTC can handle asymmetrical constraints and invariant sets unlike previous work in the literature.

In [48] the authors proposed an observer-based switching mechanism for active robust fault tolerant fuzzy control of T-S fuzzy wind turbine model under sensor faults, wind disturbances and parametric uncertainties. Stability was guaranteed by using LMIs and Taylor series. The proposed work showed that it was able to control the plant over varied range of wind speeds and stabilize the system under fault sensors and uncertainties up to 35% compared with previous work. Also, it showed increased robustness compared with conventional controllers such as PI and LQG. However, the proposed work has a limitation since there was spike developed when fault was detected. As future recommended work by the authors, a fuzzy proportional-integral observer design shall be used under the influence of parameter uncertainties and time varying sensor faults for the T-S fuzzy model.

In [35], the authors proposed a fault tolerant T-S fuzzy dynamic output feedback tracking controller for T-S four local linear multiple model 4.8 MW wind turbine in the low wind speed range to achieve tracking the optimal rotor speed and load reductions based on L_2 norm minimization for drive train torsion angle. The FTC strategy is developed such that the controller is maintained the same during fault and fault free scenarios by using TS proportional state

estimator augmented with proportional and integral feedback fault estimator which can handle additive time varying faults. To hide the effects of the sensor faults from the controller inputs, PPIO was used successfully to handle time varying faults. Stability was guaranteed using H_∞ performance and D-stability constraints formulated via LMI.

In [49], the authors proposed a robust multiplicative fault estimation for the actuator faults in the presence of exogenous disturbance and output sensor measurement noise with unknown input decoupling and H_∞ optimization on LTI wind turbine model. The proposed observer is Unknown Input Decoupling Proportional Integral observer (UI-decoupling PIO). It is difficult to estimate a multiplicative fault; hence, modification was used to convert the multiplicative fault into additive one to be able to estimate them. Also, for better estimation, the observer poles were regulated by using D stability all of which were formed via linear matrix inequalities.

In [50], [51], [13] and [15], the main author made a lot of work to create a benchmark model for a 4.8 MW wind turbine model in the context of fault diagnosis and tolerant abilities which made this benchmark well known in the literature for researchers to implement the various techniques of FDD schemes. Also, a list of various faults was listed that covers sensor, actuator and system faults. In addition, the wind turbine model was enhanced to include the wind shear and tower shadow effect. However, other WT benchmark models were developed and one of the famous models is 5 MW offshore wind turbine developed by NREL and used also as a benchmark model in control and fault tolerant control researches.

In [39], unknown input observer was used to estimate the actuator faults subject to disturbances for a linear parameter varying benchmark model [13] and [15]. The observer gains were obtained using LMI and LME. The stability and convergence of the UIO was based on $\mathcal{H}_\infty$ and Lyapunov

theories. However, only constant faults were considered but could handle those with bounded derivatives. The time varying parameter in the LPV model is assumed bounded. The disturbance and faults assumed with bounded first derivative. An active fault tolerant control was designed based on baseline PI controller and adding compensating control signal to handle actuator fault and disturbances. Wind turbine benchmark model was considered and showed good results especially for an actuator fault with constant faults such as an offset. So, to improve this work, simultaneous sensor and actuator faults shall be considered. Also, different structure of faults shall be studied considering advanced methodologies instead of relying on baseline PI controller structure and compensating the faulty signals.

In [52], proportional integral observer was used to estimate actuator faults for a nonlinear system described by T-S fuzzy system with fault tolerant capability. The robust stability of the proposed system was derived using Lyapunov and $\mathcal{L}_2$ optimization in terms of LMI and the gains of proposed FTC found from those LMI's. T-S representation of the nonlinear system was done using nonlinear sector transformation which is considered an exact representation of the overall system without loss of information. Since under fault conditions the weighing functions were different due to premise variables are not maintained, a reference T-S model without faults was formulated and reference trajectory errors with fault estimation were handled by the FTC to generate the required control input to the system. However, the faults considered as constant faults or slowly time varying faults; but if they were not, it was proposed to use proportional multiple integral observer (PMIO) instead. Future research was recommended from authors to study the case where the weighing functions are unmeasurable like the states of the system which allows for simultaneous estimation for actuator and sensor faults subjected to modeling uncertainties and disturbances.

In [40], this work proposed an active fault tolerant control for actuator of a wind turbine benchmark model and used adaptive filters based on nonlinear geometric approach (NLGA) which has the decoupling capability to deal with uncertainty of the system including disturbance, measurement noise and modeling errors. This was done by coordinate transformation under fault detectability conditions. The adaptive filter is based on least squares algorithm with forgetting factor. The nonlinearity of the system was represented by mapping of power coefficients with tip speed ratio and pitch angles approximated by using look up tables. So due to the difficulty of analytical to represent the power conversion map, it was estimated along with fault tolerant strategy with disturbance decoupling. The power coefficient estimation deals with problem and blade wear and debris build up on rotor blades. There were 6 actuator faults conditions considered 5 of which on pitch actuator and one on converter torque. However, the assumed faults for adaptive filter are constant faults only. A baseline PI controller was implemented and sampled at 100 Hz. Comparison among different fault estimation techniques were implemented namely sliding mode observer and neural network estimators.

In [36], a fault tolerant control for a T-S fuzzy based model of an offshore wind turbine was implemented to handle sensor faults during low wind speed; hence, pitch subsystem was not considered since the pitch angle is kept at zero. The objective of this work was to maintain the controller structure during fault and fault free cases. The fault estimation scheme used an observer augmented with proportional integral feedback to estimate rotor and generator speed sensors faults. The proposed scheme can estimate time varying faults with assumption of bounded first derivative for each fault. Moreover, the difference of wind speed measurement from anemometer and unmeasurable effective wind speed was considered. Also, a T-S fuzzy dynamic output feedback controller was designed for tracking optimal rotor speed and load reduction in the drive-train

subsystem by minimizing $\mathcal{L}_2$ norm of wind variation on torsion angle of drivetrain. The stability was proved using $\mathcal{D}$ -stability constraints and $\mathcal{H}_\infty$ performance and formulated using LMI in which observer and controller poles for each T-S model were in region of a disc in the complex plane.

In [53], the authors designed a nonlinear unknown input observer as a fault estimation scheme along with fuzzy scheduler FTC for a T-S fuzzy system of wind turbine system with doubly fed induction generator (DFIG) subjected to time varying unknown inputs, parametric uncertainties and sensor faults. Parallel distributed compensation was used to design the fuzzy scheduler FTC and fuzzy observers from the T-S fuzzy system model. The robust stability was proved using Taylor series and Lyapunov method for the T-S fuzzy system considering sensor faults, uncertainties and unknown inputs formulated in LMI form. However, the authors did not consider actuator faults.

In [54], the authors developed a control allocation approach in case of blade actuator failure especially for over actuated system. The concept of control allocation is to redistribute the torque to the non-faulty actuators in order to maintain power output from wind turbine with minimal interruption. Integral absolute error was implemented to measure the performance of the compensation technique for 4.8 MW benchmark wind turbine model with PI controller and it showed satisfactory results.

In [55], the authors developed a model reference based adaptive fault tolerant controller to handle time varying actuator failures, modeling uncertainties and external disturbances for an individual blade pitch control of a wind turbine. The controller technique is based on radial basis function with neural network (RBF-NN) which helped in approximating the unknown upper bound of the uncertainties. A linear relation between the input and output of NN with online updated weights.

However, three FTC schemes were implemented including the proposed one. First, robust FTC depending on the available upper bound on the lumped uncertainties. Second, robust adaptive FTC with adaptive adjustment of unknown upper bound parameter. The proposed algorithm worked effectively; but sensor faults were not considered.

In [56], the authors developed two FTC schemes to regulate generator torque subject to actuator faults in converter/generator only, model uncertainties, measurement noises and wind turbulences. First, a fuzzy model reference adaptive control without exact knowledge of the faults, disturbances and uncertainties which does not require fault detection and diagnosis scheme which is considered as passive FTC approach. Second, fuzzy identification and modeling used for an integrated model-based fault diagnosis with automatic signal correction mechanism which is considered as an active FTC approach. Both schemes were implemented in 5 MW NREL offshore wind turbine and showed good robustness under fault and fault-free condition for the entire range of wind profiles. However, wide range of faults including sensor faults were not considered.

In [41], an integrated FDD and FTC scheme were formulated by designing an active fault tolerant control with automatic signal correction to an improved fuzzy gain scheduled PI collective pitch controller to handle sensor faults for generator speed and blade pitch angle under wind turbulences and measurement noises for 5 MW NREL offshore wind turbine. Such FTC systems are considered as active FTC since fault estimation was needed to tune the controller parameters online but did not require reconfiguration of controller structure.

In [42], the authors proposed a baseline PI controller with a fault compensating strategy to handle only pitch actuator faults. The state and fault estimation were achieved by implementing an adaptive step by step sliding mode observer which handles time varying nonlinear fault distribution

function which was different than other fault estimation observers like adaptive observer, sliding model observer, extended state observer and unknown input observer. Since adaptive approach is incorporated in the design of sliding mode observer a priori knowledge of the bound of estimation errors and first derivative of fault indicator is not needed. So, reconfiguration of controller is implemented once set by the fault indicator and system relied on the baseline PI controller. All the three pitch systems have same dynamics and considered that all have the same control input acting on all three pitch actuators (collective pitch control). So, it was recommended to consider individual pitch control as it helps in blade load reduction.

In [57], a wind turbine system based on doubly fed induction generator with actuator faults and disturbances was considered. Takagi-Sugeno based modeling was used to approximate the model. The original system was decomposed using linear transformation into three subsystem and used also T-S fuzzy observer and distribution estimation techniques.

In [58], the authors developed an active FTC scheme to control rotor speed and power of a 5 MW benchmark wind turbine model subject to actuator faults and matched uncertainties using a full order compensator for disturbance and fault attenuation and using adaptive output feedback sliding mode controller based on the collective pitch control approach. There were two methods to design the subject controller as reported in this work: through state observer or directly using output of the system for controller design and second approach was applied. The proposed work was compared with PID and disturbance accommodation control (DAC) methods. The proposed scheme was robust with less fluctuations than PID-LQR and DAC methods; however, DAC performed better than PID based method. However, in this study only overrated wind speed was considered and only actuator faults were considered. It was recommended to design a switching mechanism between below rated wind speed and overrated wind speed.

2.5 Takagi Sugeno Based Modeling

To understand the T-S fuzzy based modeling, fuzzy logic concepts are important to be understood. Fuzzy logic-based system was developed to enhance the control performance for systems with highly complex or nonlinear system. This is done by having fuzzy rules using IF-THEN rules which covers the possible conditions of the operating envelope of the plant and using functions to give a degree of membership for different fuzzy sets instead of only having one set. Afterwards, the output is aggregated to represent the overall system based on its input arguments. Figure 10 shows the basic configuration of fuzzy logic control.

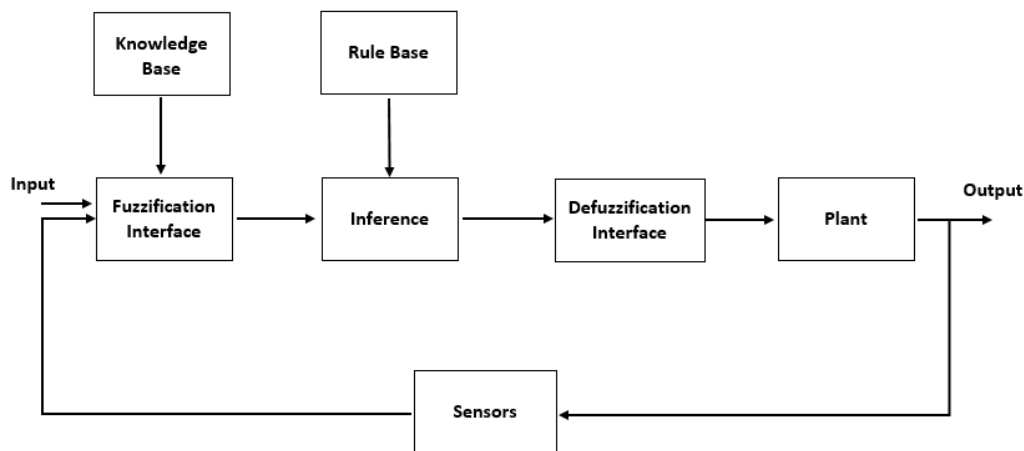


Figure 10: Basic Setup of Fuzzy Logic Control

However, the fuzzy implications used in T-S fuzzy modeling approach is based on partitioning the input space into several fuzzy partitions where each partition is having a linear relationship between input and output. The output is the aggregation of all values resulted from the implication for each subspace partition. The importance of T-S fuzzy modeling approach emerges when operator experience or control engineer cannot describe linguistically the required output action at

certain situations. Also, when the operator's action is not believed to be optimal to achieve the objectives and requirements; as a result, numerical approach is needed using fuzzy modeling [60].

It is noticed that T-S fuzzy system has a format of implication with unconditioned premises are omitted, only “and” operator which stands for minimum operation with linear consequence function and the fuzzy implication R is in the following format:

$$R: \text{if } x_1 \text{ is } A_1 \text{ and } \dots \text{ and } x_k \text{ is } A_k$$

$$\text{Then, } y = p_0 + p_1 x_1 + \dots + p_k x_k$$

For modeling, Takagi-Sugeno fuzzy modeling technique has shown great performance for approximating, analyzing and synthesizing nonlinear and complex system and widely implemented in different engineering and non-engineering applications due to its concepts that are easy to understand and implement. So, T-S fuzzy based modeling approach is merely based on combination of linearized models of the original plant at different operating point.

However, in [61] to model a nonlinear system the authors have developed a fuzzy based technique that highly approximate the nonlinear complex model by aggregating multiple local linearized model which have been implemented in many engineering applications and specifically in wind turbine systems in references [43], [33], [47], [48] and [35].

Generally, there are two approaches to get T-S fuzzy modeling: analytical based method using sector nonlinearity and data-based method using input/output data. However, so much researches have been done to improve the T-S fuzzy modeling approach by optimizing the number of fuzzy rules, membership functions, etc.

Briefly, the Takagi-Sugeno Fuzzy modeling approach for general nonlinear system using if-then rules can take the following form:

If μ_1 is M_{1i} and μ_q is M_{qi} , then

$$\begin{cases} \dot{x}(t) = A_i x(t) + B_i u(t) + B_{di} d(t) + B_{fi} f(t) \\ y(t) = C x(t) + D_d d_w(t) + D_f f(t) \end{cases} \quad (2.1)$$

Where $d(t)$ and $d_w(t)$ are the bounded unknown disturbances from the plant and sensor; respectively, $u(t)$ is the control input; $x(t)$ is the state of the system; $y(t)$ is the measured output; $f(t)$ is vector combining both actuator and sensor fault; M_{ji} are fuzzy sets and μ represents the decision vector contain all individual known premise variables which could be function of external inputs, state variables and time, $i = 1, 2, \dots, r$ which indicates the number of local models to approximate the general nonlinear plant and usually it depends on the modeling accuracy, plant complexity and membership function structure.

Nevertheless, T-S fuzzy modeling is basically aggregating the consequences due to the different degree of membership function in different operating points that spans the overall working operating conditions of the system; hence, equation becomes

$$\begin{cases} \dot{x}(t) = \sum_{i=1}^r h_i(\mu) [A_i x(t) + B_i u(t) + B_{di} d(t) + B_{fi} f(t)] \\ y(t) = C x(t) + D_d d_w(t) + D_f f(t) \end{cases} \quad (2.2)$$

where $h_i(\mu)$ are weighting functions that measures the membership degree of the current operating point at a certain zone of operation. So, Equation (2.2) represents the T-S fuzzy model of a general nonlinear system with several local linearized model that are aggregated through weighting functions depending on the operation point of the system. T-S fuzzy system has good advantage since it has smooth connection among different local models of the nonlinear system which reduce

transients in system; hence, improving its performance and avoid unnecessary abrupt and degradation in system's performance.

2.6 Issues with Existing Methodologies

The drawbacks and concerns related to the existing methodologies in literature are presented:

- Focused mostly on linearized models with less attention on nonlinear models.
- Focused either on sensor or actuator faults with less attention on simultaneous faults.
- Most of fault types are time-invariant faults with less work on time varying faults including time delays imposed on the system.
- Effective wind speed estimation was not considered in FTC schemes.
- Few researches considered system parameter uncertainties.
- There are two general schemes in blade pitch control: collective pitch control (CPC) and individual pitch control (IPC). CPC approach was mostly considered in literature with less attention on IPC approach.
- Very few papers considered optimizing the Takagi-Sugeno fuzzy modeling system to accurately approximate the actual nonlinear system.
- Control switching modes between both operating conditions (partial and full load operation) was not addressed adequately in fault tolerant schemes.
- Comparative analysis among fault estimation techniques on wind turbine applications generally was not addressed adequately even though it was applied in other applications.

- No researches adequately focused on optimizing the parameters of fault estimators such as UIO and SMO in wind turbine system.

CHAPTER 3

Wind Turbine Systems

3.1 Introduction

There are two main different wind turbine types in terms of orientation and energy capturing technique: vertical axis wind turbine (VAWT) based on drag force and horizontal axis wind turbine (HAWT) based on the lift force. HAWT usage has increased dramatically due to the advantages over the VAWT; hence vast amount of research is being done in HAWT for larger power production. For more details about the difference, one can refer to [11]. Figure 11 shows the vertical and horizontal axis wind turbine. In this chapter, a mathematical model of the wind turbine will be presented.

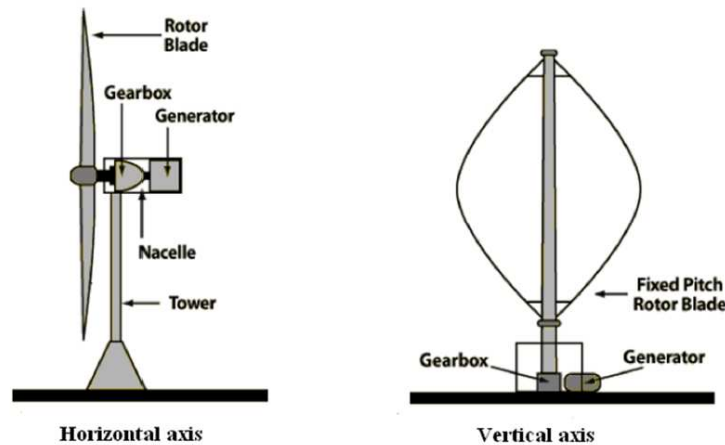


Figure 11: Horizontal and Vertical Axis Wind Turbine [12]

In this chapter, a mathematical model of the wind turbine will be presented.

3.2 Description and Modeling of Wind Turbine

The model of wind turbine that will be studied in this thesis work is a benchmark model established by [13]. It is a three-blade-horizontal variable speed wind turbine with a full converter and its rated power is 4.8 MW.

Before highlighting the model for wind turbine, its functional description is presented. The principle of wind turbine is to generate power from wind as the wind turns the blade of the wind turbine, the wind turbine rotor will turn accordingly. This mechanical rotation is then converted into electrical energy utilizing a generator with converter.

However, the energy, and hence the rotating shaft, can be controlled by adjusting the aerodynamics of the turbine through pitching the angles of the blades. Also, there is a drive train that is connected between the rotor of wind turbine and the generator.

Since the rotation speed of wind turbine is slow but with high torque, the existence of drive train is important to increase the rotational speed of the shaft connected to the generator side to produce enough amount of energy.

In addition, the converter plays a role in setting the generator torque to control the rotational shaft speed of the generator to its designed and operating limits. The main control objective of wind turbine in full load operation is to track power reference. Figure 12 shows the components of a wind turbine.

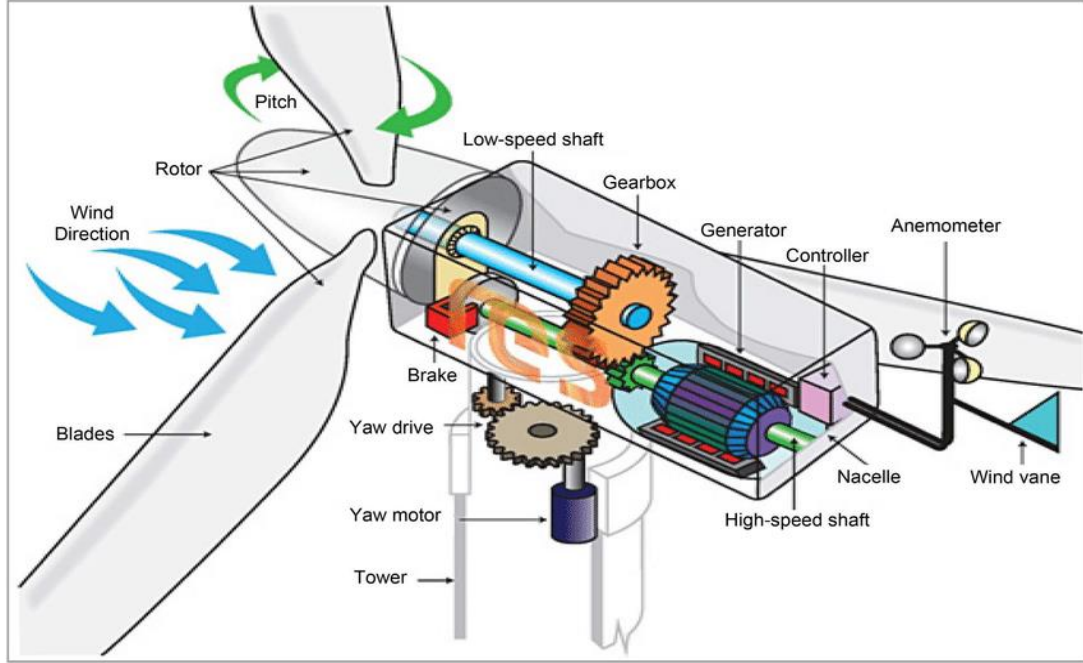


Figure 12: Three Blade-Horizontal-Axis-Wind Turbine Components [14]

The wind turbine is divided into subsystems as follows: blade and pitch subsystem, drive train subsystem, generator and converter subsystem as shown in Figure 13. Refer to Table 2 for parameters description.

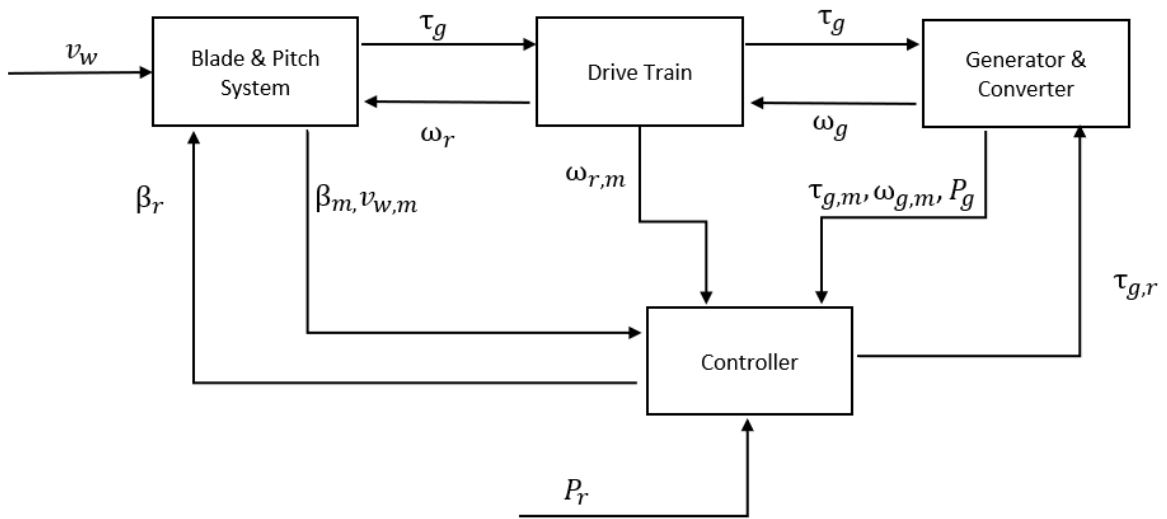


Figure 13: Wind Turbine Block Diagram

Table 2: Model Parameters [15]

Parameter	Description	Parameter	Description
P_r	Rated power	J_g	Generator inertia (high speed shaft)
α	Empirical wind shear exponent	η_g	Efficiency of generator
H	Hub height	α_{gc}	Generator and converter parameter
R	Radius of rotor	τ_r	Aerodynamic torque
ρ	Air density	C_q	Torque coefficient
ζ	Damping factor	θ_Δ	Drive train torsion angle
ω_n	Natural frequency	τ_g	Generator torque
B_{dt}	Torsion damping coefficient	ω_r	Angular speed of rotor
K_{dt}	Torsion stiffness	ω_g	Angular speed of generator
J_r	Rotor inertia (low speed shaft)	λ	Tip speed ratio
B_r	Rotor external damping	β	Blade pitch angle
B_g	Generator external damping	v_w	Wind speed
η_{dt}	Drive train efficiency	P_g	Generated power
N_g	Gearbox ratio	v_m	Mean wind speed

The detailed modeling for each subsystem is presented in the following subsections starting with wind model. In addition, this model is close to the real system specially that it considers wind shear and tower shadow effects in the wind turbine model.

3.2.1 Wind Model

Wind can be represented as stochastic behavior with tower shadow and wind shear effects. The combined wind model has several types of winds that are considered in this context [15]:

$$v_w(t) = v_m(t) + v_s(t) + v_{ws}(t) + v_{ts}(t) \quad (3.1)$$

$v_m(t)$ is the mean of wind speed which represents the slow variations of wind and obtained by having a sequence of wind data and processed with low pass filter; $v_s(t)$ is the stochastic behavior of wind and obtained by using Kaimal filters ; $v_{ws}(t)$ represents the wind shear effect and $v_{ts}(t)$ represents the wind tower shadow which are both described in detail below.

The wind shear is basically representing the wind speed variations depending on the height and mathematically can be described as:

$$v_{ws}(t) = \frac{2v_m(t)}{3R^2} \left\{ \left(\frac{\alpha R^3}{3H} \cos(\theta_{r^*(t)}) + \frac{R^4}{4} \alpha \frac{\alpha-1}{2H^2} \cos(\theta_{r^*(t)})^2 \right) + \left(\frac{R^5}{5} \frac{(\alpha^2-\alpha)(\alpha-2)}{6H^3} \right) \cos(\theta_{r^*(t)})^3 \right\} \quad (3.2)$$

For simplicity, Equation (3.2) is rearranged as:

$$v_{ws}(t) = \frac{2\alpha R v_m(t)}{9H} \cos(\theta_{r^*(t)}) + \frac{\alpha(\alpha-1)R^2 v_m(t)}{12H^2} \cos(\theta_{r^*(t)})^2 + \frac{(\alpha^2-\alpha)(\alpha-2)R^3 v_m(t)}{45H^3} \cos(\theta_{r^*(t)})^3$$

where θ_{r^*} is the position angles of the three blades and α with H are aerodynamic parameters which are namely empirical wind shear component and hub height; respectively.

The tower shadow effect accounts for blade passing in front of the wind turbine tower and mathematically can be described as:

$$v_{ts,i}(t) = \frac{m \bar{\theta}_{r,i}(t)}{3r^2} (\psi + v) \quad (3.3)$$

where

$$\psi = 2a^2 \frac{R^2 - r_0^2}{(R^2 + r_0^2) \sin(\bar{\theta}_{r,i}(t))^2 + k^2} \quad (3.4)$$

$$v = 2a^2 k^2 \frac{(r_0^2 - R^2) \sin(\bar{\theta}_{r,i}(t))^2 + k^2}{R^2 \sin(\bar{\theta}_{r,i}(t))^2 + k^2} \quad (3.5)$$

$$m = 1 + \frac{\alpha(\alpha-1)r_0^2}{8H^2} \quad (3.6)$$

$$\bar{\theta}_{r,i}(t) = \theta_{r(t)} + \frac{2\pi(i-1)}{3} - \left\lfloor \left(\frac{\theta_{r(t)} + \frac{2\pi(i-1)}{3}}{2\pi} \right) \right\rfloor 2\pi \quad (3.7)$$

Where k represents the distance from the tower midline to the blade origin; r_0 represents radial distance from the hub center to the blades; a represents the tower radius and i represents blade number.

3.2.2 Blade and Pitch Subsystem

The aerodynamic torque model is considered as part of the blade and pitch subsystem and modeled as torque τ_r acting on the blades and mathematically is driven as:

$$\tau_r(t) = \frac{\rho \pi R^3 C_q(\lambda(t), \beta(t)) v_w^2(t)}{2} \quad (3.8)$$

where $C_q(\lambda(t), \beta(t))$ is mapping that shows the dependence on tip speed ratio and pitch angle in the torque coefficients.

However, in order to have different pitch angles for the blades the model becomes:

$$\tau_r(t) = \sum_{i=1}^3 \frac{\rho \pi R^3 C_q(\lambda(t), \beta(t)_i) v_w^2(t)}{6} \quad (3.9)$$

This model is valid only for small differences in the pitch angles. For the pitch system model, it is a hydraulic based on a piston servo system and it is described as a second order transfer function:

$$\frac{\beta(s)}{\beta_r(s)} = \frac{\omega_n^2}{s^2 + 2\zeta\omega_n s + \omega_n^2} \quad (3.10)$$

where ω_n is the natural frequency and ζ is the damping factor; those two parameters will change if a fault occurs in this subsystem.

The time domain and state space form for the pitch system is derived from equation (3.10) as below:

$$\ddot{\beta} + \dot{\beta}2\zeta\omega_n + \beta\omega_n^2 = \beta_r\omega_n^2$$

Assuming state variables $\check{x}_1$ and $\check{x}_2$ equal β and $\dot{\beta}$; respectively, this implies:

$$\check{x}_1 = \check{x}_2$$

$$\dot{\check{x}}_2 = \ddot{\beta} = \beta_r\omega_n^2 - \check{x}_2 2\zeta\omega_n - \check{x}_1\omega_n^2$$

Arranging it in state space form:

$$\begin{bmatrix} \dot{\check{x}}_1 \\ \dot{\check{x}}_2 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ -\omega_n^2 & -2\zeta\omega_n \end{bmatrix} \begin{bmatrix} \check{x}_1 \\ \check{x}_2 \end{bmatrix} + \begin{bmatrix} 0 \\ \omega_n^2 \end{bmatrix} \beta_r$$

The state space model can be represented as:

$$\begin{bmatrix} \dot{\beta} \\ \ddot{\beta} \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ -\omega_n^2 & -2\zeta\omega_n \end{bmatrix} \begin{bmatrix} \beta \\ \dot{\beta} \end{bmatrix} + \begin{bmatrix} 0 \\ \omega_n^2 \end{bmatrix} \beta_r ; y = [1 \quad 0] \begin{bmatrix} \beta \\ \dot{\beta} \end{bmatrix} \quad (3.11)$$

3.2.3 Drive Train Subsystem

The drive train is modeled as a two-mass model system which includes a gearbox to transfer the energy from low shaft speed of rotor to high shaft speed of generator as shown in the Figure 14.

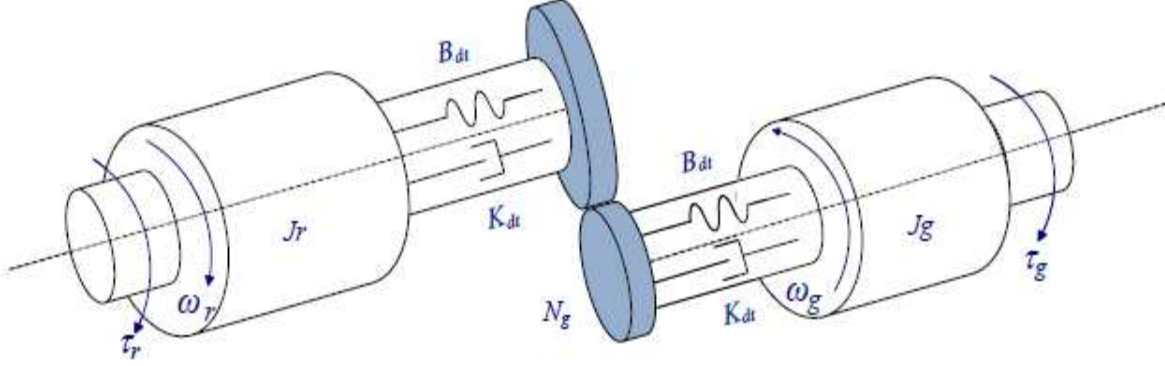


Figure 14: Two-Mass Model for Drive-Train Subsystem [16]

$$J_r \dot{\omega}_r(t) = \tau_r(t) - K_{dt} \theta_{\Delta}(t) - (B_{dt} - B_r) \omega_r(t) + \frac{B_{dt}}{N_g} \omega_g(t) \quad (3.12)$$

$$J_g \dot{\omega}_g(t) = \frac{\eta_{dt} K_{dt}}{N_g} \theta_{\Delta}(t) + \frac{\eta_{dt} B_{dt}}{N_g} \omega_r(t) - \left(\frac{\eta_{dt} B_{dt}}{N_g^2} + B_g \right) \omega_g(t) - \tau_g(t) \quad (3.13)$$

$$\dot{\theta}_{\Delta}(t) = \omega_r(t) - \frac{1}{N_g} \omega_g(t) \quad (3.14)$$

Arranging the above equations in state space form results in the following:

$$\begin{bmatrix} \dot{\omega}_r(t) \\ \dot{\omega}_g(t) \\ \dot{\theta}_{\Delta}(t) \end{bmatrix} = \begin{bmatrix} -\frac{(B_{dt}+B_r)}{J_r} & \frac{B_{dt}}{N_g J_r} & -\frac{K_{dt}}{J_r} \\ \frac{\eta_{dt} B_{dt}}{N_g J_g} & \frac{\eta_{dt} B_{dt} - B_g N_g^2}{N_g^2 J_g} & \frac{\eta_{dt} K_{dt}}{N_g J_g} \\ 1 & -\frac{1}{N_g} & 0 \end{bmatrix} \begin{bmatrix} \omega_r(t) \\ \omega_g(t) \\ \theta_{\Delta}(t) \end{bmatrix} + \begin{bmatrix} \frac{1}{J_r} & 0 \\ 0 & \frac{-1}{J_g} \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \tau_r(t) \\ \tau_g(t) \end{bmatrix};$$

$$y = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} \omega_r(t) \\ \omega_g(t) \\ \theta_{\Delta}(t) \end{bmatrix} \quad (3.15)$$

where J_r is the low speed shaft inertia moment; J_g is the high speed shaft inertia moment; B_{dt} is the torsion damping coefficient of drive train; B_g is the high speed shaft viscous friction; K_{dt} is the

drive train torsion stiffness; N_g is the gear ratio, $\theta_{\Delta}(t)$ is the drive train torsion angle; η_{dt} is the drive train efficiency; ω_g is the angular rotation of generator shaft and ω_r is the angular rotation of rotor shaft.

3.2.4 Generator and Converter Subsystem

The power produced by the generator is described as

$$P_g(t) = \eta_g \omega_g(t) \tau_g(t) \quad (3.16)$$

The converter dynamics is modeled as a first order transfer function:

$$\frac{\tau_g(s)}{\tau_{g,r}(s)} = \frac{\alpha_{gc}}{s + \alpha_{gc}} \quad (3.17)$$

where $\tau_{g,r}$ represents generator torque; η_g represents the generator efficiency and α_{gc} represents converter and generator parameter.

3.2.5 Overall Augmented System Model:

An augmented system of the overall subsystem is formulated. The aerodynamic torque:

$$\tau_r(t) = \frac{\rho \pi R^3 C_q(\lambda(t), \beta(t)) v_w^2(t)}{2} \quad (3.18)$$

However, tip speed ratio depends on wind speed and rotor speed.

$$\lambda = \frac{\omega_r R}{v_w} \Rightarrow v_w = \frac{\omega_r R}{\lambda} \quad (3.19)$$

Substituting (3.19) into aerodynamic torque (3.18) yields to:

$$\tau_r(t) = \frac{\rho \pi R^3 C_q(\lambda(t), \beta(t)) (\frac{\omega_r R}{\lambda})^2}{2} = \frac{\rho \pi R^5 C_q(\lambda(t), \beta(t)) \omega_r^2}{2 \lambda^2} \quad (3.20)$$

From the drive train subsystem, the rotor speed is:

$$\dot{\omega}_r(t) = -\frac{(B_{dt} + B_r)}{J_r} \omega_r + \frac{1}{J_r} \tau_r(t) \quad (3.21)$$

Inserting the aerodynamic torque in (3.20) into (3.21), results in:

$$\dot{\omega}_r(t) = -\frac{(B_{dt} + B_r)}{J_r} \omega_r + \frac{1}{J_r} \left(\frac{\rho \pi R^5 C_q(\lambda(t), \beta(t)) \omega_r^2}{2\lambda^2} \right)$$

Taking ω_r as common factor:

$$\dot{\omega}_r(t) = \left[-\frac{(B_{dt} + B_r)}{J_r} + \frac{1}{J_r} \left(\frac{\rho \pi R^5 C_q(\lambda(t), \beta(t)) \omega_r}{2\lambda^2} \right) \right] \omega_r$$

$$\dot{\omega}_r(t) = \left[-\frac{(B_{dt} + B_r)}{J_r} + \frac{1}{2J_r \lambda^2} (\rho \pi R^5 C_q(\lambda(t), \beta(t)) \omega_r) \right] \omega_r \quad (3.22)$$

This completes the drive train subsystem, now augmenting all subsystems results in:

$$\begin{cases} \dot{x} = A(x)x + Bu \\ y = Cx \end{cases}$$

where the augmented state vector $x = [\omega_r \quad \omega_g \quad \theta_\Delta \quad \dot{\beta} \quad \beta \quad \tau_g]^T$ and $u = [\tau_{g,r} \quad \beta_r]^T$ is the control input reference vector generated by a pre-designed controller. In full load operation, the objective is to control both pitch angle and generator torque to regulate the generated power under physical constraints.

However, in partial load operation the pitch angle is always set at 0 and then only generator torque controller is active to maximize the power captured from available wind power. Effectively the torque coefficient is dependent on three parameters namely wind speed, rotor speed and pitch angle

and they represent the nonlinear part of the model which is basically the aerodynamic torque.

Equation (3.23) shows the details of the overall augmented model

$$\begin{aligned}
 \begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \\ \dot{x}_3 \\ \dot{x}_4 \\ \dot{x}_5 \\ \dot{x}_6 \end{bmatrix} &= \begin{bmatrix} \Gamma & \frac{B_{dt}}{N_g J_r} & -\frac{K_{dt}}{J_r} & 0 & 0 & 0 \\ \frac{\eta_{dt} B_{dt}}{N_g J_g} & \frac{\frac{\eta_{dt} B_{dt}}{N_g^2} B_g}{J_g} & \frac{\eta_{dt} K_{dt}}{N_g J_g} & 0 & 0 & \frac{-1}{J_g} \\ 1 & \frac{-1}{N_g} & 0 & -2\zeta\omega_n & -\omega_n^2 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \\ x_6 \end{bmatrix} + \\
 \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ \omega_n^2 & 0 \\ 0 & 0 \\ 0 & \alpha_{gc} \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} \\
 y &= \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \\ x_6 \end{bmatrix} \tag{3.23}
 \end{aligned}$$

Where Γ is given by $-\frac{(B_{dt}+B_r)}{J_r} + \frac{1}{2J_r\lambda^2} (\rho\pi R^5 C_q(\lambda(t), \beta(t))\omega_r)$.

Now, Equation (3.23) represents the overall augmented system of wind turbine system combining all subsystem models with nonlinear aerodynamic part of the system.

Table 3 shows the model parameters and variables of benchmark wind turbine model.

Table 3: Model Parameters of Benchmark Wind Turbine [13]

Parameter	Description	Value
P_r	Rated power	4.8 MW
α	Empirical wind shear exponent	0.1
H	Hub height	81 m
R	Radius of rotor	57.5 m
ρ	Air density	1.225 kg/m^3
ζ	Damping factor	0.6
ω_n	Natural frequency	11.11 rad/s
B_{dt}	Torsion damping coefficient	775.49 N.m.s/rad
K_{dt}	Torsion stiffness	$2.7 \times 10^9 \text{ N.m/rad}$
J_r	Rotor inertia (low speed shaft)	$55 \times 10^6 \text{ kg.m}^2$
B_r	Rotor external damping	7.11 N.m.s/rad
B_g	Generator external damping	45.6 N.m.s/rad
η_{dt}	Drive train efficiency	0.97
N_g	Gearbox ratio	95
J_g	Generator inertia (high speed shaft)	390 kg.m^2
η_g	Efficiency of generator	0.98
α_{gc}	Generator and converter parameter	50 rad/s

3.3 Control Concepts

In order to control any system, it is mandatory to understand how the system operates and what need to be controlled and main objective of control as well. Wind turbine goes through four operational zones that depends on the mean wind speed value. Those operating zones are illustrated in the power performance curve as shown in Figure 15. Zone 1 and 4 are not considered in the fault diagnosis and control scheme since at these zones the wind turbine is stopped due to low wind speed in zone 1 and high wind speed in zone 4 which are limited by the cut-in speed and cut-out speed depending on wind turbine design; respectively. In zone 2, wind speed lies between 3 to 12.5 m/s and which is considered as partial load power capacity of wind turbine and the objective of the control scheme in this zone is to ensure power optimization. However, in zone 3, the wind speed lies between 12.5 m/s and 25 m/s but ideally with a constant power production; therefore, the control objective at this zone is to regulate the power.

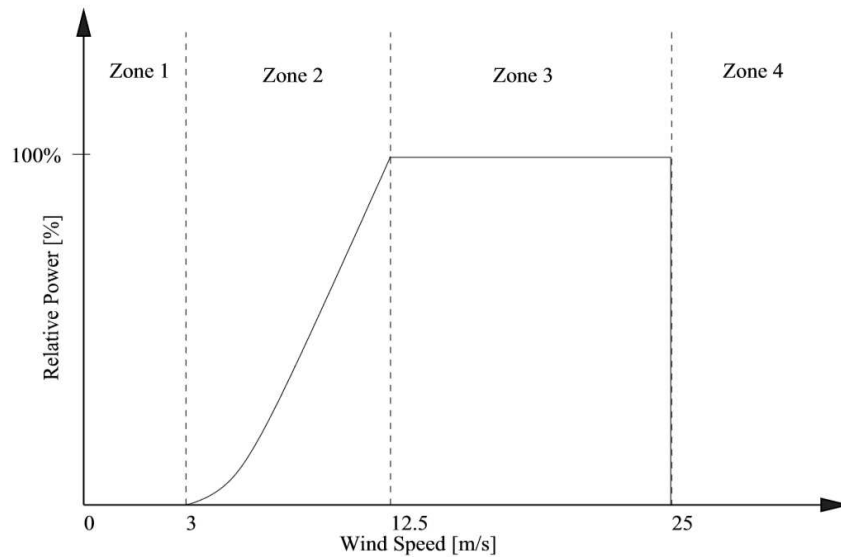


Figure 15: Power Curve for Wind Turbine at Different Wind Speed Ranges [15]

The tip speed ratio λ is defined as

$$\lambda = \frac{w_r R}{v_w} \quad (3.24)$$

The optimal value of tip speed ratio λ_{opt} is at which maximum power coefficient is obtained at pitch angle equal to zero. Figure 16 and 17 shows the concept of the optimal tip speed ratio.

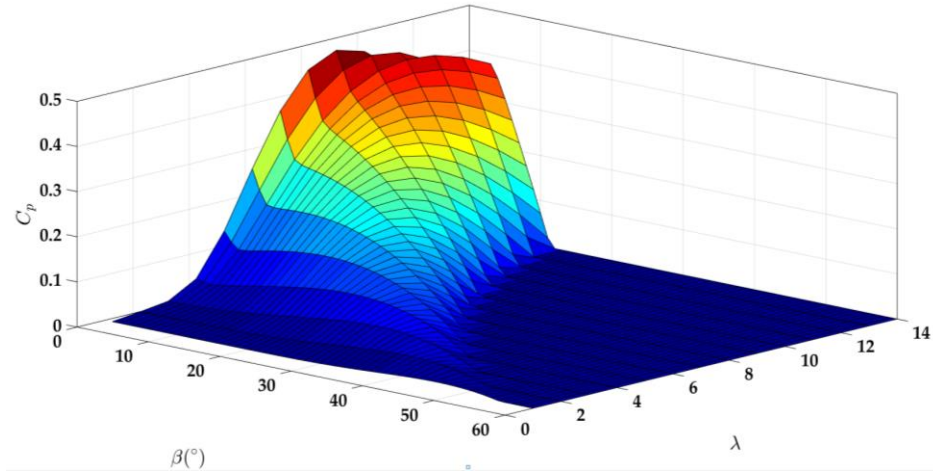


Figure 16: Power Coefficient at Different Pitch Angle and Tip Speed Ratio [51]

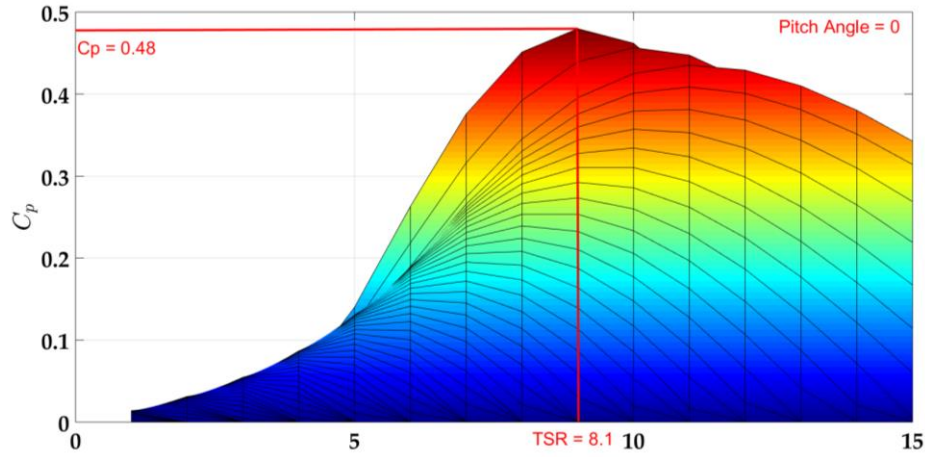


Figure 17: Optimal Tip Speed Ratio (TSR) at Pitch Angle = 0 with maximum C_p of 0.48 [51]

As a result, to control the generator torque of the wind turbine, the reference torque $\tau_{g,r}$ is sent to the converter and defined during power optimization in Zone 2 as:

$$\tau_{g,r} = K_{opt} w_r^2 \quad (3.25)$$

$$K_{opt} = \frac{1}{2} \rho A R^3 \frac{C_p^{max}}{\lambda_{opt}^3} \quad (3.26)$$

While at Zone 3, the objective is to track the power reference as required by controlling the blade pitch angle reference signal such that power coefficient C_p is decreased which basically keeping angular speed of the rotor w_r at its rated values [13]. Figure 18 shows region 2 and 3 in terms of real wind speed profile.

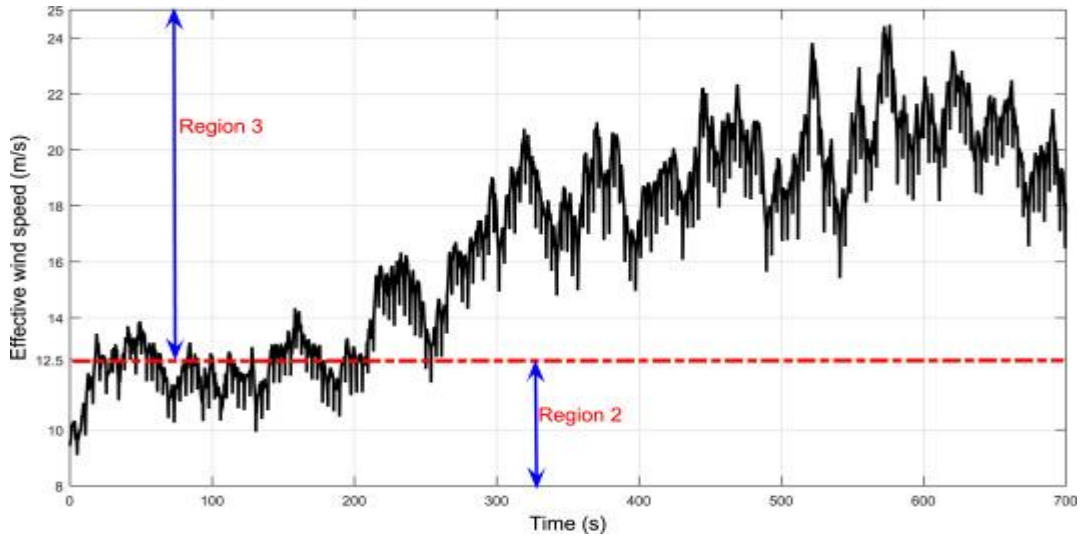


Figure 18: Operating Zone 2 and 3 Based on Wind Speed Measurement or Estimation [17]

3.4 Fault Types, Scenarios and Conditions

In this thesis, several faults will be considered namely sensor, actuator and system faults. Those faults conditions are additive and multiplicative faults in nature as well as including changing in the dynamics of the system. The fault conditions and scenarios represent actual faults with different level of severity. Faults are classified based on their time characteristics into three classes as shown in Figure 19.

However, in the subsequent sections, faults are classified based on their location and behavior. Based on the time characteristics, faults can be either abrupt, incipient or intermittent. Abrupt faults occur suddenly with large step changes either higher or lower than nominal values. However, incipient faults are slowly changing in their values but could increase at very large values with slow rate of change. For intermittent faults, they occur for short duration of time that could not be noticed depending on system configuration and application.

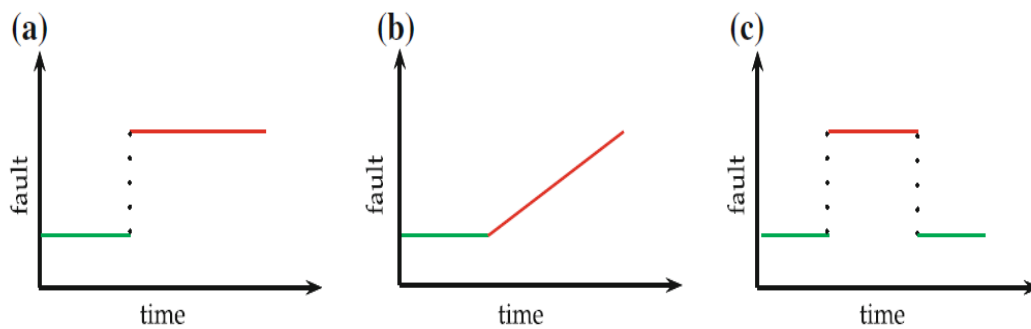


Figure 19: Fault Types: (a) Abrupt, (b) Incipient and (c) Intermittent [62]

3.5 Sensor Faults

Sensor faults covers all different kind measurements with wind turbine system mainly pitch position, rotor speed and generator speed sensors. For pitch position sensor, the fault is originated from either mechanical or electrical fault which in turn results in either a fixed or changed gain factor on the sensor measurements.

Similarly, rotor and generator speed sensors are based on encoders and results on a static or changed gain on the measurements. Those faults are originated from improper readings of the encoder due to, for example, dirt which would result in a gain factor on the measurement.

Figure 20 shows different types of sensor faults: bias, freezing, drift, loss of accuracy and calibration error.

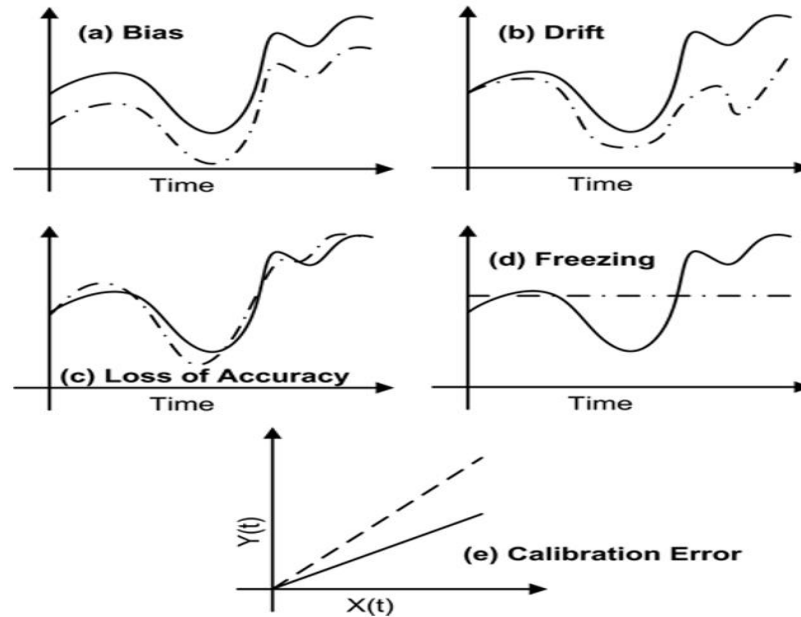


Figure 20: Types of Sensor Faults [63]

3.6 Actuator Faults

The actuator system is divided into two classes: electrical actuator and mechanical actuator. The electrical actuator in this system can be the converter. Its fault condition results in dynamic change due to converter electronics problems or an offset due to converter torque problems. The mechanical actuator in the system is related to hydraulic pitch system to control the pitch angle of the blades. The two main faults in this system originates from either high air content or drop pressure in the hydraulic oil system. Figure 21 shows different types of faults in actuators which includes lock in place, float, hard-over and loss of effectiveness.

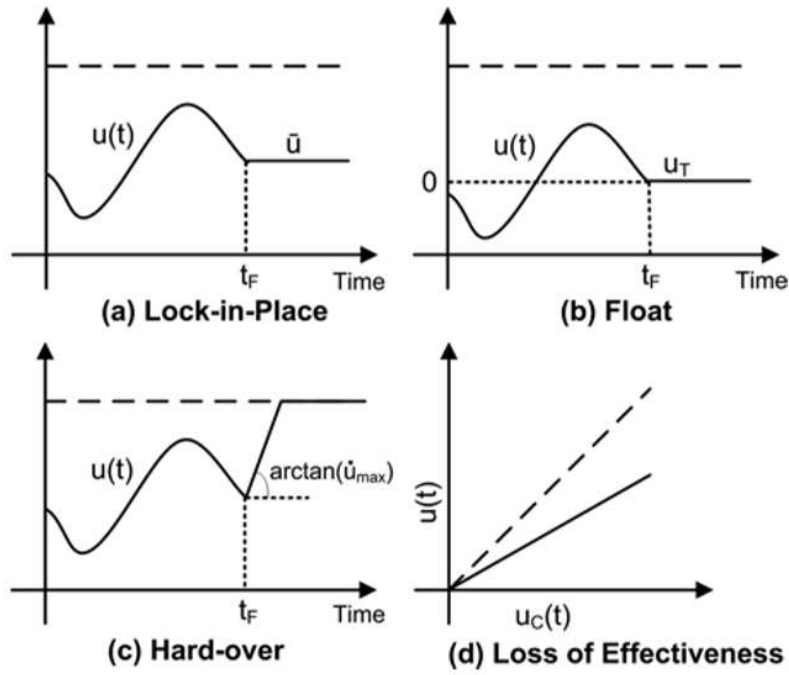


Figure 21: Types of Actuator Faults [63]

3.7 System Faults

The benchmark system faults considered for wind turbine occur in the drive train subsystem and the fault mainly originates from friction coefficient which slowly changes with time and takes long time to develop and results in a correlated change in rotor and generator speed. Table 4 shows a benchmark of fault scenario and conditions at different time periods between 2000 to 4300 seconds which is widely used in the literature.

Table 4: Fault Scenario and Conditions [13]

Fault No.	Fault Location	Fault Condition	Values	Time Duration (s)
1	Pitch Sensor	Fixed Value	5°	2000-2100
2	Pitch Sensor	Gain Factor	$1.2 * \beta_m$	2300-2400
3	Rotor Speed Sensor	Fixed Value	1.4 rad/s	1500-1600
4	Rotor Speed Sensor	Gain Factor	$1.1 * \omega_r$	1000-1100
5	Generator Speed Sensor	Gain Factor	$0.9 * \omega_g$	1000-1100
6	Converter Actuator Fault	Offset	$\tau_g + 100 Nm$	3800-3900
7	Pitch Actuator 2 Fault (hydraulic oil)	Changed Dynamic	$\omega_n * \zeta_2$	2900-3000
8	Pitch Actuator 3 Fault (air in oil)	Changed Dynamic	$\omega_{n3} * \zeta_3$	3500-3600
9	System Fault	Changed Dynamic	$\Delta\omega_g, \Delta\omega_r$	4100-4300

3.8 Summary

In this chapter, mathematical derivation for all subsystems of the wind turbine was developed and the model to be used in this thesis is given by Equation (3.23). Also, the wind model was developed to closely represent actual wind behavior by considering wind shear and tower shadow effect. The wind model to be used in this thesis is given by Equation (3.1). Finally, the faults considered in the simulations are listed in Table 5.

Table 5: Fault Conditions Considered in Simulation

Fault No.	Fault Location	Fault Condition	Values	Time Duration (s)
1	Generator Torque	Fixed	2000 N.m	300-500 s
2	Generator Torque	Fixed	5000 N.m	700-900 s
3	Pitch Actuator	Offset	10° C	900-1100 s
4	Generator Torque	Fixed	4000 N.m	300-500 s
5	Generator Torque	Fixed	10,000 N.m	700-900 s

CHAPTER 4

Thesis Work

4.1 Methodology

In this research, T-S fuzzy for wind turbine system is proposed to handle specifically the nonlinearity of aerodynamic torque which is based on tip speed ratio, blade pitch angle and rotor angular speed. Also, different estimation techniques are proposed to estimate the aerodynamic torque and torque coefficient to avoid wind speed sensors and compared among all techniques. Moreover, an advanced observer based on unknown input observer is proposed to estimate simultaneously the system's states and faults during wind turbine operation. In addition, an adaptive fault tolerant control scheme is proposed to accommodate faults in the generator subsystem during partial load operation of wind turbine while maintaining the reliability and efficiency of the system to produce power. Then, a comparative analysis is conducted between a baseline controller and adaptive fault tolerant controller under fault-free case and fault cases to show the effectiveness of the proposed control system to accommodate faults and maintain power production.

4.2 Aerodynamic Torque Estimation Techniques During Partial Load Operation of Wind Turbine

In this thesis, several estimation techniques are presented and compared in terms of error difference between actual and estimated parameter. Two different set up are implemented. One is estimating

the aerodynamic torque coefficient as this is the nonlinear part of the model. In this context, the torque coefficient is estimated $C_q(\lambda(t), \beta(t))$ alone then aerodynamic is calculated using Equation (3.8). This means that $\lambda(t)$ and $\beta(t)$ used as input regressors. However, $\beta(t)$ in this context is zero since the work is focused during partial load operation in which pitch angle reference is zero to capture maximum available energy. The other scenario is to estimate the aerodynamic torque $\tau_r(t)$ directly in which rotor speed ω_r and wind speed v_w are used as input regressors to the estimator. The estimation techniques that are implemented include the following:

1. Takagi-Sugeno fuzzy model-based estimation (T-S Fuzzy)
2. Recursive least squares-based estimation using forgetting factor (RLS-FF)
3. Recursive least squares-based estimation using Kalman filter (RLS-KF)
4. Recursive least squares-based estimation using normalized gradient (RLS-NG)
5. Recursive least squares-based estimation using un-normalized gradient. (RLS-UNG)

4.2.1 Takagi-Sugeno Fuzzy Model Based Estimation

T-S fuzzy modeling technique has shown great performance for approximating, analyzing and synthesizing nonlinear and complex system and widely implemented in different engineering and non-engineering applications. Briefly, the T-S Fuzzy modeling approach for general nonlinear system using if-then rules can take the following form:

If μ_1 is M_{1i} and μ_q is M_{qi} ; then

$$\begin{cases} \dot{x}(t) = A_i x(t) + B_i u(t) \\ y(t) = C_i x(t) + D_i u(t) \end{cases} \quad (4.1)$$

where $u(t)$ is the control input; $x(t)$ is the state of the system; $y(t)$ is the measured output; M_{ji} are fuzzy sets and μ represents the decision vector that contains all individual known premise variables which could be function of external inputs, state variables and time, $i = 1, 2, \dots, r$ which indicates the number of local models to approximate the general nonlinear plant and usually it depends on the modeling accuracy, plant complexity and membership function structure.

$$\begin{cases} \dot{x}(t) = \sum_{i=1}^r h_i(\mu) [A_i x(t) + B_i u(t) + B_{di} d(t) + B_{fi} f(t)] \\ y(t) = Cx(t) + D_d d_w(t) + D_f f(t) \end{cases} \quad (4.2)$$

where $h_i(\mu)$ are weighting functions that measures the membership degree of the current operating point at a certain zone of operation.

In the T-S Fuzzy based approach, the decision variables were selected due to their role in introducing the nonlinear behavior in aerodynamic torque which are tip speed ration, blade pitch angle and rotor speed. Those are considered the premise variables which constitute for a set of local operation modes. The rotor speed w_r is divided into 2 fuzzy sets, blade pitch angle β is divided into 4 fuzzy sets and tip speed ratio λ is divided into 3 fuzzy sets as shown in Equation (4.3), (4.4) and (4.5), respectively.

The membership functions were designed as follows:

$$\begin{bmatrix} a_1(w_r) \\ a_2(w_r) \end{bmatrix} = \begin{bmatrix} \frac{w_2 - w_r}{w_2 - w_1} \\ \frac{w_r - w_1}{w_2 - w_1} \end{bmatrix} \quad (4.3)$$

$$\begin{bmatrix} b_1(\beta) \\ b_2(\beta) \\ b_3(\beta) \\ b_4(\beta) \end{bmatrix} = \begin{bmatrix} \frac{N_2 - \beta}{2(N_2 - N_1)} \operatorname{sgn}(N_2 - \beta) + \frac{N_2 - \beta}{2(N_2 - N_1)} \\ \frac{\beta - N_1}{2(N_2 - N_1)} \operatorname{sgn}(N_2 - \beta) + \frac{\beta - N_1}{2(N_2 - N_1)} + \frac{N_3 - \beta}{2(N_3 - N_2)} \operatorname{sgn}(\beta - N_2) \operatorname{sgn}(N_3 - \beta) + \frac{N_3 - \beta}{2(N_3 - N_2)} \\ \frac{\beta - N_2}{2(N_3 - N_2)} \operatorname{sgn}(N_3 - \beta) \operatorname{sgn}(\beta - N_2) + \frac{\beta - N_2}{2(N_3 - N_2)} + \frac{N_4 - \beta}{2(N_4 - N_3)} \operatorname{sgn}(\beta - N_3) + \frac{N_4 - \beta}{2(N_4 - N_3)} \\ \frac{\beta - N_3}{2(N_4 - N_3)} \operatorname{sgn}(\beta - N_3) + \frac{\beta - N_3}{2(N_4 - N_3)} \end{bmatrix} \quad (4.4)$$

$$\begin{bmatrix} C_1(\lambda) \\ C_2(\lambda) \\ C_3(\lambda) \end{bmatrix} = \begin{bmatrix} \frac{V_2 - \lambda}{2(V_2 - V_1)} \operatorname{sgn}(V_2 - \lambda) + \frac{V_2 - \lambda}{2(V_2 - V_1)} \\ \frac{\lambda - V_1}{2(V_2 - V_1)} \operatorname{sgn}(V_2 - \lambda) + \frac{\lambda - V_1}{2(V_2 - V_1)} + \frac{V_3 - \lambda}{2(V_3 - V_2)} \operatorname{sgn}(\lambda - V_2) + \frac{V_3 - \lambda}{2(V_3 - V_2)} \\ \frac{\lambda - V_2}{2(V_3 - V_2)} \operatorname{sgn}(\lambda - V_2) + \frac{\lambda - V_2}{2(V_3 - V_2)} \end{bmatrix} \quad (4.5)$$

Where sgn is

$$\operatorname{sgn}(x) = \begin{cases} -1 & x < 1 \\ 0 & x = 0 \\ 1 & x > 1 \end{cases}$$

And $W_1 = 0.0591, W_2 = 2.5, N_1 = -2, N_2 = 5, N_3 = 35, N_4 = 70, V_1 = 1, V_2 = 13, V_3 = 13$ represent the set of local operation modes which results in at total of 24 local operation modes. The final global membership function is found by multiplying the sub membership function. All membership functions should range between 0 and 1 and the summation of sub-membership function for each decision variable must equal to one. All above designed membership functions are satisfying the requirement and final global membership function is $h_{ltk} = a_l * b_t * c_k$

4.2.2 Recursive Least Squares Estimation

The universal method of the infinite-history recursive estimation algorithms is:

$$\hat{\theta}(t) = \hat{\theta}(t-1) + K(t)(y(t) - \hat{y}(t)) \quad (4.6)$$

where $\hat{\theta}(t)$ is the estimated parameter; $y(t)$ is the observed output; $\hat{y}(t)$ is the predicted output; $K(t)$ is the gain which is designed to minimize the prediction error by updating the parameter estimate based on error magnitude.

The gain is formulated as:

$$K(t) = Q(t)\psi(t) \quad (4.7)$$

All recursive algorithms are similar, but they are different on how to design $Q(t)$ and $\psi(t)$. In this thesis, $\psi(t)$ denotes the gradient of the predicted output $\hat{y}(t|\theta)$ with respect to the parameters θ .

Considering models with linear regression form:

$$y(t) = \psi^T(t)\theta_0(t) + e(t) \quad (4.8)$$

where $\psi(t)$ is the regression vector that is calculated based on prior values of measured inputs and outputs and $\theta_0(t)$ represents the true parameters while $e(t)$ is the source of noise called innovations and assumed to be white noise.

The predicted output is given by the following formula:

$$\hat{y}(t) = \psi^T(t)\theta_0(t-1) \quad (4.9)$$

In sections below, all estimation algorithms implemented in this context is based on recursive least squares estimation but with different adaptation algorithms of $Q(t)$

4.2.3 Recursive Least Squares Estimation based on Forgetting Factor

The below set of equations are for recursive least square estimation based on forgetting factor adaptation algorithm:

$$Q(t) = \frac{P(t-1)}{\lambda + \psi^T P(t-1) \psi(t)} \quad (4.10)$$

$$P(t) = \frac{1}{\lambda(t)} \left(P(t-1) - \frac{P(t-1) \psi(t) \psi^T P(t-1)}{\lambda(t) + \psi^T P(t-1) \psi(t)} \right) \quad (4.11)$$

The forgetting factor $\lambda(t)$ affects the estimation performance as shown in (4.12)

$$\sum_{k=1}^t \lambda^{t-k} (y(k) - \hat{y}(t))^2 \quad (4.12)$$

This algorithm is relied on reducing the weight on old measurement values. Setting the forgetting factor to 1 is mainly to estimate constant parameters and less than 1 for time varying parameters but typically not less than 0.9 and it also depends on the application.

As the forgetting factor becomes smaller, the smaller is the influence of preceding samples to the covariance matrix. This enables the estimator to be more sensitive to latest samples. This results in variations and instabilities in the estimator coefficients. When $\lambda = 1$, it is referred to as the growing window RLS algorithm. In this simulation, the forgetting factor was set to 1.

4.2.4 Recursive Least Squares Estimation based on Kalman Filter

The below set of equations are for recursive least squares estimation based on Kalman filter adaptation algorithm:

$$Q(t) = \frac{P(t-1)}{R_2 + \psi^T P(t-1) \psi(t)} \quad (4.13)$$

$$P(t) = P(t-1) + R_1 - \frac{P(t-1) \psi(t) \psi^T P(t-1)}{R_2 + \psi^T P(t-1) \psi(t)} \quad (4.14)$$

In Kalman based adaptation algorithm, $P(t)$ is calculated while assuming the residuals are white noise and their variance is equal to one.

$Q(t)$ is computed using Kalman based algorithm and true parameters are described as:

$$\theta_0(t) = \theta_0(t-1) + w(t) \quad (4.15)$$

$$y(t) = \psi^T(t)\theta_0(t) + e(t) \quad (4.16)$$

where $w(t)$ is white Gaussian noise with a covariance matrix of R_1 :

$$E w(t)w^T(t) = R_1 \quad (4.17)$$

Where R_2 is the variance of prediction error term $e(t)$:

$$E e(t)e^T(t) = R_2 \quad (4.18)$$

The Kalman filter algorithm is completely quantified by $y(t)$, the gradient $\psi(t)$, R_1 , R_2 , the initial conditions $P(t=0)$ parameter covariance matrix that indicates parameters errors and $\theta(t=0)$ initial guess of the parameters. In this framework, the process noise covariance is set to 1 and parameter noise covariance is set to 100.

4.2.5 Recursive Least Squares Estimation based on Un-normalized Gradient Algorithm

In the un-normalized gradient approach, $Q(t)$ is given by:

$$Q(t) = \gamma \quad (4.19)$$

Where γ is the adaptation gain and was set to 1.

4.2.6 Recursive Least Squares Estimation based on Normalized Gradient Algorithm

In the normalized gradient approach, which considered as one of recursive prediction error methods is given by:

$$Q(t) = \frac{\gamma}{|\psi(t)|^2 + \text{Bias}} \quad (4.20)$$

This algorithm gauges the adaptation gain, γ , at each step. However, when the gain is scaled by only the squared norm of the gradient, this may result in jumps and sudden changes in the estimated parameters. Therefore, a bias term was introduced as indicated in equation (4.20) which avoids division by zero when the gradient becomes effectively zero. If observed jumps in the estimated parameters, then Bias has to be increased. In this context, it is equal to $2.2204\text{e-}16$ and γ equal to 1.

4.3 Simultaneous State and Fault Estimation using Unknown Input Observer

The subject system is in the following form:

$$\begin{aligned} \dot{x}(t) &= Ax(t) + Bu(t) + B_d d(t) + B_f f(t) \\ y(t) &= Cx(t) + D_d d_w(t) + D_f f(t) \end{aligned} \quad (4.21)$$

Where $d(t)$ and $d_w(t)$ are the bounded unknown disturbances from the plant and sensor; respectively, $u(t)$ is the control input; $x(t)$ is the state of the system; $y(t)$ is the measured output; $B_d = [B_{d1} \ B_{d2}]$ and $d = [d_1 \ d_2]^T$ where d_1 can be decoupled; $f(t)$ is vector combining both actuator and sensor fault. The faults assumed to be abrupt or incipient. For those faults which have second order derivative not equal to zero but bounded, those bounded signals are considered as unknown inputs and thus f and $\dot{f}$ are assumed bounded.

In order to estimate both states and faults simultaneously, an augmented system is formed by combining fault vectors with system's states. This implies that augmented state $\bar{x}(t) = [x \ \dot{f} \ f]^T$ which results in the following augmented system:

$$\begin{cases} \dot{\bar{x}} = \bar{A}\bar{x} + \bar{B}u + \bar{B}_d d \\ y = \bar{C}\bar{x}(t) + D_d d_w(t) \end{cases} \quad (4.22)$$

where the augmented matrices are:

$$\bar{A} = \begin{bmatrix} A_{n \times n} & 0_{n \times l_f} & B_f \\ 0_{l_f \times n} & 0_{l_f \times l_f} & 0_{l_f \times l_f} \\ 0_{l_f \times n} & I_{l_f} & 0_{l_f \times l_f} \end{bmatrix} \in \mathcal{R}^{\bar{n} \times \bar{n}}, \bar{B} = \begin{bmatrix} B \\ 0 \\ 0 \end{bmatrix} \in \mathcal{R}^{\bar{n} \times m}, \bar{B}_d = \begin{bmatrix} B_d \\ 0 \\ 0 \end{bmatrix} \in \mathcal{R}^{\bar{n} \times l_d}, \bar{C} = [C \quad 0 \quad D_f] \in \mathcal{R}^{p \times \bar{n}}$$

$\bar{n} = n + 2l_f$; where l_f is the dimension of fault vector including actuator and sensor, l_d dimension of unknown input vector.

4.3.1 Full Order Unknown Input Observer Framework

The subject system is in the following form:

$$\begin{cases} \dot{\bar{z}} = R\bar{z} + T\bar{B}u + (K_1 + K_2)y \\ \hat{\bar{x}} = \bar{z} + Hy \end{cases} \quad (4.23)$$

Where $\hat{\bar{x}} \in \mathcal{R}^{\bar{n}}$ is the estimated augmented state vector, $\bar{z} \in \mathcal{R}^{\bar{n}}$ is the state of the observer, and other gain matrices R, T, H, K_1 and K_2 to be designed to achieve unknown input decoupling and estimation of states and faults simultaneously.

Then, the estimation error can be formulated as $\bar{e} = \bar{x} - \hat{\bar{x}}$, where $\bar{x}$ is the state of the augmented system (4.22) and $\hat{\bar{x}}$ is the state estimate of the augmented system obtained using UIO (4.23). So, error dynamics derivate $\dot{\bar{e}}$ can be calculated as shown below:

$$\bar{e} = \bar{x} - \hat{\bar{x}} \Rightarrow \dot{\bar{e}} = \dot{\bar{x}} - \dot{\hat{\bar{x}}} \quad (4.24)$$

From (4.22) and (4.23):

$$\dot{e} = \bar{A}\bar{x} + \bar{B}u + \bar{B}_d d - (\dot{\bar{z}} + H\dot{y}) \Rightarrow$$

$$\dot{e} = \bar{A}\bar{x} + \bar{B}u + \bar{B}_d d - (R\bar{z} + T\bar{B}u + (K_1 + K_2)y + H\dot{y}) \quad (4.25)$$

While $y = \bar{C}\bar{x}(t) + D_d d_w(t)$, then its derivative is

$$\dot{y} = \bar{C}\dot{\bar{x}} + D_d \dot{d}_w \quad (4.26)$$

Inserting (4.26) into (4.25) results in:

$$\dot{e} = \bar{A}\bar{x} - H\bar{C}\dot{\bar{x}} + \bar{B}u - T\bar{B}u + \bar{B}_d d - R\bar{z} - K_1 y - K_2 y - H D_d \dot{d}_w \quad (4.27)$$

Inserting $\dot{\bar{x}}$ from (4.22) into (4.27) results in:

$$\dot{e} = (I - H\bar{C})\bar{A}\bar{x} + (I - H\bar{C} - T)\bar{B}u + (I - H\bar{C})\bar{B}_d d - R\bar{z} - K_1 y - K_2 y - H D_d \dot{d}_w \quad (4.28)$$

Inserting y from (4.22) into (4.28) results in:

$$\begin{aligned} \dot{e} = & (I - H\bar{C})\bar{A}\bar{x} + (I - H\bar{C} - T)\bar{B}u + (I - H\bar{C})\bar{B}_d d - R\bar{z} - K_1 \bar{C}\bar{x} - K_1 D_d d_w - K_2 \bar{C}\bar{x} - \\ & K_2 D_d d_w - H D_d \dot{d}_w \end{aligned} \quad (4.29)$$

where $\bar{B}_d = [B_d^T \ 0 \ 0]^T$; $B_d = [B_{d1} \ B_{d2}]$; $d = [d_1 \ d_2]^T$ and d_1 can be decoupled, then with substitution into (4.29) results in:

$$\begin{aligned} \dot{e} = & (\bar{A} - H\bar{C}\bar{A} - K_1 \bar{C})\bar{x} - K_1 \bar{C}\bar{x} + (I - H\bar{C} - T)\bar{B}u + (I - H\bar{C})\bar{B}_{d1} d_1 + (I - H\bar{C})\bar{B}_{d2} d_2 - \\ & R\bar{z} - K_1 D_d d_w - K_2 \bar{C}\bar{x} - K_2 D_d d_w - H D_d \dot{d}_w \end{aligned} \quad (4.30)$$

Since $\bar{e} = \bar{x} - \hat{\bar{x}} \Rightarrow \bar{e} = \bar{x} - (\bar{z} + Hy) \Rightarrow \bar{e} = \bar{x} - \bar{z} - Hy$ which implies that

$$\bar{x} = \bar{e} + \bar{z} + Hy \quad (4.31)$$

Then, inserting (4.31) into (4.30) results in:

$$\dot{\bar{e}} = (\bar{A} - H\bar{C}\bar{A} - K_1\bar{C})\bar{e} + (\bar{A} - H\bar{C}\bar{A} - K_1\bar{C} - R)\bar{z} + [(\bar{A} - H\bar{C}\bar{A} - K_1\bar{C})H - K_2]y + (I - H\bar{C} - T)\bar{B}u + (I - H\bar{C})\bar{B}_{d1}d_1 + (I - H\bar{C})\bar{B}_{d2}d_2 - K_1D_d d_w - HD_d \dot{d}_w \quad (4.32)$$

From equation (4.32), the error dynamics can be reduced by cancelling the terms $\bar{z}$, u , y and d_1 , (but not d_2 since it is uncoupled disturbance) if the following conditions of the observer gains are met:

$$1) \{(I - H\bar{C})\bar{B}_{d1} = 0\} \quad (4.33)$$

$$2) (\bar{A} - H\bar{C}\bar{A} - K_1\bar{C} - R) = 0 \Rightarrow \{R = \bar{A} - H\bar{C}\bar{A} - K_1\bar{C}\} \quad (4.34)$$

$$3) (I - H\bar{C} - T) = 0 \Rightarrow \{T = I - H\bar{C}\} \quad (4.35)$$

$$4) (\bar{A} - H\bar{C}\bar{A} - K_1\bar{C})H - K_2 = 0 \Rightarrow K_2 = (\bar{A} - H\bar{C}\bar{A} - K_1\bar{C})H \Rightarrow \{K_2 = RH\} \quad (4.36)$$

Then, error dynamics represented by (4.29) can be reduced to:

$$\dot{\bar{e}} = R\bar{e} + (I - H\bar{C})\bar{B}_{d2}d_2 - K_1D_d d_w - HD_d \dot{d}_w \quad (4.37)$$

To meet the above 4 conditions on the observer gains, the below assumptions are considered, which are namely the necessary and sufficient conditions for UIO existence:

$$\text{i) } \text{Rank}(\bar{C}B_{d1}) = \text{rank}(B_{d1})$$

$$\text{ii) } \text{rank} \begin{bmatrix} sI_n - A & B_{d1} \\ C & 0 \end{bmatrix} = n + l_{d1}$$

$$\text{iii) } \text{full column rank of } \begin{bmatrix} A & B_f & B_{d1} \\ C & D_f & 0 \end{bmatrix}$$

Condition (i) ensures that (4.30) can be solved with special solution of matrix H while condition (ii) ensures that the pair $((\bar{C}, \bar{A}_d)$ is detectable where $\bar{A}_d = (I - H\bar{C})\bar{A}$.

The error dynamics still has d_w and d_2 which are the uncoupled unknown disturbances, therefore, using convex based optimization using linear matrix inequality with Lyapunov stability theorems.

The candidate Lyapunov function $V(\bar{e}) = \bar{e}^T P \bar{e}$ where the function should be positive definite, and its derivative is negative definite to guarantee error convergence.

$$\dot{V}(\bar{e}) = \dot{\bar{e}}^T P \bar{e} + \bar{e}^T P \dot{\bar{e}} \quad (4.38)$$

From (4.35) $T = I - H\bar{C}$; and for two matrices $(AB)^T = B^T A^T$; then (4.38) becomes:

$$\begin{aligned} \dot{V}(\bar{e}) = & [\bar{e}^T R^T P \bar{e} + (TB_{d2}d_2)^T P \bar{e} - (K_1 D_d d_w)^T P \bar{e} - (H D_d \dot{d}_w)^T P \bar{e} + \bar{e}^T P R \bar{e} + \\ & \bar{e}^T P T B_{d2} d_2 - \bar{e}^T P K_1 D_d d_w - \bar{e}^T P H D_d \dot{d}_w] \end{aligned} \quad (4.39)$$

From (4.34), inserting R into (4.39)

$$\begin{aligned} \dot{V}(\bar{e}) = & [\bar{e}^T (\bar{A}^T T^T P - \bar{C}^T K_1^T P + P T \bar{A} - P K_1 \bar{C}) \bar{e} + 2\bar{e}^T P T B_{d2} d_2 - 2\bar{e}^T P K_1 D_d d_w - \\ & 2\bar{e}^T P H D_d \dot{d}_w] \end{aligned} \quad (4.40)$$

From (4.35) inserting T into (4.40)

$$\begin{aligned} \dot{V}(\bar{e}) = & [\bar{e}^T (A^T P - \bar{A}^T \bar{C}^T H^T P - \bar{C}^T K_1^T P + P A - P H \bar{C} \bar{A} - P K_1 \bar{C}) \bar{e} + 2\bar{e}^T P T B_{d2} d_2 - \\ & 2\bar{e}^T P K_1 D_d d_w - 2\bar{e}^T P H D_d \dot{d}_w] \end{aligned} \quad (4.41)$$

A change of variable is made and special solution of matrix H

$$Y = P K_1 \quad (4.42)$$

$$H = \bar{B}_{d1} (\bar{C} \bar{B}_{d1}^+)^+ + N [I - (\bar{C} \bar{B}_{d1}) (\bar{C} \bar{B}_{d1}^+)^+] \quad (4.43)$$

Inserting (4.42) and (4.43) into (4.41) results in:

$$\begin{aligned}\dot{V}(\bar{e}) = & [\bar{e}^T (\bar{A}^T P - \bar{A}^T \bar{C}^T [\bar{B}_{d1}(\bar{C}\bar{B}_{d1}^+) + N[I - (\bar{C}\bar{B}_{d1})(\bar{C}\bar{B}_{d1}^+)]]^T P - \bar{C}^T Y^T + P\bar{A} - \\ & [PB_M(\bar{C}\bar{B}_{d1}^+) + PN[I - (\bar{C}B_M)(\bar{C}\bar{B}_{d1}^+)]] \bar{C}\bar{A} - Y\bar{C})\bar{e} + 2\bar{e}^T PTB_{d2}d_2 - 2\bar{e}^T PK_1D_d d_w - \\ & 2\bar{e}^T PHD_d \dot{d}_w] \end{aligned} \quad (4.44)$$

Change of variable is done as detailed below:

$$Z = PN \quad (4.45)$$

$$G = I - (\bar{C}B_M)(\bar{C}\bar{B}_{d1}^+) \quad (4.46)$$

Inserting (4.45) and (4.46) into (4.44) results in:

$$\begin{aligned}\dot{V}(\bar{e}) = & [\bar{e}^T (\bar{A}^T P - \bar{A}^T \bar{C}^T [B_M(\bar{C}\bar{B}_{d1}^+) + N[I - (\bar{C}\bar{B}_{d1})(\bar{C}\bar{B}_{d1}^+)]]^T P + P[I - \\ & B_M(\bar{C}\bar{B}_{d1}^+)\bar{C}]\bar{A} - ZG\bar{C}\bar{A} - Y\bar{C} - \bar{C}^T Y^T)\bar{e} + 2\bar{e}^T PTB_{d2}d_2 - 2\bar{e}^T PK_1D_d d_w - \\ & 2\bar{e}^T PHD_d \dot{d}_w] \end{aligned} \quad (4.47)$$

Change of variable is done as detailed below:

$$F = I - B_M(\bar{C}\bar{B}_{d1}^+)\bar{C} \quad (4.48)$$

Inserting (4.49) into (4.48) results in:

$$\begin{aligned}\dot{V}(\bar{e}) = & [\bar{e}^T (\bar{A}^T F^T P - \bar{A}^T \bar{C}^T G^T Z^T + PF\bar{A} - ZG\bar{C}\bar{A} - Y\bar{C} - \bar{C}^T Y^T)\bar{e} + 2\bar{e}^T PTB_{d2}d_2 - \\ & 2\bar{e}^T PK_1D_d d_w - 2\bar{e}^T PHD_d \dot{d}_w] \end{aligned} \quad (4.49)$$

For the second term $2\bar{e}^T PTB_{d2}d_2$, where $T = I - H\bar{C}$ and $H = B_M(\bar{C}\bar{B}_{d1}^+) + N[I - (\bar{C}\bar{B}_{d1})(\bar{C}\bar{B}_{d1}^+)]$, Then, (4.49) becomes:

$$\dot{V}(\bar{e}) = [\bar{e}^T (\bar{A}^T F^T P - \bar{A}^T \bar{C}^T G^T Z^T + PFA - ZG\bar{C}A - Y\bar{C} - \bar{C}^T Y^T) \bar{e} + 2\bar{e}^T (PF - ZG\bar{C})B_{d2}d_2 - 2\bar{e}^T YD_d d_w - 2\bar{e}^T (PB_M(\bar{C}B_M^+) + PN[I - (\bar{C}B_M)(\bar{C}B_M^+)])D_d \dot{d}_w] \quad (4.50)$$

where $Q = \bar{C}B_{d2}^+$; (4.50) becomes:

$$\Rightarrow \dot{V}(\bar{e}) = [\bar{e}^T (\bar{A}^T F^T P - \bar{A}^T \bar{C}^T G^T Z^T + PF\bar{A} - ZG\bar{C}\bar{A} - Y\bar{C} - \bar{C}^T Y^T) \bar{e} + 2\bar{e}^T (PF - ZG\bar{C})B_{d2}d_2 - 2\bar{e}^T YD_d d_w - 2\bar{e}^T (PB_{d2}Q + ZG)D_d \dot{d}_w] \quad (4.51)$$

Note that

$$1- 2\bar{e}^T (PF - ZG\bar{C})B_{d2}d_2 = \bar{e}^T (PF - ZG\bar{C})B_{d2}d_2 + ((PF - ZG\bar{C})B_{d2}d_2)^T \bar{e} \quad (4.52)$$

$$2- 2\bar{e}^T YD_d d_w = \bar{e}^T (YD_d d_w) + (YD_d d_w)^T \bar{e} \quad (4.53)$$

$$3- 2\bar{e}^T (PB_M Q + ZG)D_d \dot{d}_w = \bar{e}^T (PB_M Q + ZG)D_d \dot{d}_w + ((PB_M Q + ZG)D_d \dot{d}_w)^T \bar{e} \quad (4.54)$$

4.3.2 Robustness of UIO Estimator

Based on H-infinity norm which is defined as a gain of system, looking for disturbance attenuation, where $\bar{e}$ is the estimation error of the augmented system; $\bar{d} = [d_2 \ d_w \ \dot{d}_w]$ and T_f is the norm order. Selecting 2-norm in this context with performance index γ results in proving the candidate Lyapunov function in (4.38) is negative definite in:

$$\Gamma = \frac{\|\bar{e}\|_{T_f}}{\|\bar{d}\|_{T_f}} < \gamma \Rightarrow \frac{\|\bar{e}\|_{T_f}^2}{\|\bar{d}\|_{T_f}^2} < \gamma^2$$

$$\Rightarrow \frac{\|\bar{e}\|_2}{\|\bar{d}\|_2} < \gamma \Rightarrow \frac{\|\bar{e}\|_2^2}{\|\bar{d}\|_2^2} < \gamma^2$$

$$\|\bar{e}\|_2^2 < \gamma^2 \|\bar{d}\|_2^2 \Rightarrow \|\bar{e}\|_2^2 - \gamma^2 \|\bar{d}\|_2^2 < 0 ; \text{ taking the integral for both sides:}$$

$$\int (\bar{e}^T \bar{e} - \gamma^2 \bar{d}^T \bar{d}) dt < 0 \quad (4.55)$$

By adding and subtracting $\int \dot{V}(\bar{e})dt$ into (4.53) results in:

$$\begin{aligned}
&\Rightarrow \Gamma = \int (\bar{e}^T \bar{e} - \gamma^2 \bar{d}^T \bar{d} + \dot{V}(\bar{e}))dt - \int \dot{V}(\bar{e})dt < 0 \\
&\Rightarrow \int (\bar{e}^T \bar{e} - \gamma^2 \bar{d}^T \bar{d} + \dot{V}(\bar{e}))dt - \int \dot{V}(\bar{e})dt < 0 \\
&\Rightarrow \int (\bar{e}^T \bar{e} + \dot{V}(\bar{e}) - \gamma^2 \bar{d}^T \bar{d})dt - \int \dot{V}(\bar{e})dt < 0
\end{aligned} \tag{4.56}$$

Substituting $\dot{V}(\bar{e})$ found in (4.52) into:

$$\begin{aligned}
&\Rightarrow \int (\bar{e}^T \bar{e} + \bar{e}^T (\bar{A}^T F^T P - \bar{A}^T \bar{C}^T G^T Z^T + PF\bar{A} - ZG\bar{C}\bar{A} - Y\bar{C} - \bar{C}^T Y^T)\bar{e} + 2\bar{e}^T (PF - \\
&ZG\bar{C})B_{d2}d_2 - 2\bar{e}^T YD_d d_w - 2\bar{e}^T (PB_M Q + ZG)D_d \dot{d}_w - \gamma^2 \bar{d}^T \bar{d})dt - \int \dot{V}(\bar{e})dt < 0 \\
&\Rightarrow \int [\bar{e}^T \quad \bar{d}^T] \Phi \begin{bmatrix} \bar{e} \\ \bar{d} \end{bmatrix} dt - \int \dot{V}(\bar{e})dt < 0
\end{aligned} \tag{4.57}$$

By substituting $\bar{d}$ by $[d_2 \quad d_w \quad \dot{d}_w]$ into (4.55):

$$\Rightarrow \int [\bar{e}^T \quad d_2^T \quad d_w^T \quad \dot{d}_w^T] \Phi \begin{bmatrix} \bar{e} \\ d_2 \\ d_w \\ \dot{d}_w \end{bmatrix} dt - \int \dot{V}(\bar{e})dt < 0 \tag{4.58}$$

By factoring out the terms as shown in (4.59), Φ is found to be:

$$\begin{bmatrix} \Lambda & (PF - ZG\bar{C})B_{d2} & YD_d & (PB_M Q + ZG)D_d \\ * & -\gamma^2 I_{ld2} & 0 & 0 \\ * & * & -\gamma^2 I_{ldw} & 0 \\ * & * & * & -\gamma^2 I_{ldw} \end{bmatrix} \tag{4.59}$$

Where $\Lambda = I + \bar{A}^T F^T P - \bar{A}^T \bar{C}^T G^T Z^T + PF\bar{A} - ZG\bar{C}\bar{A} - \bar{C}^T Y^T - Y\bar{C}$

Therefore, to satisfy the robustness of the estimator (4.58)

, $\Phi < 0$ which is basically a linear matrix inequality that can be solved using LMI solvers and tools such as LMI MATLAB toolbox.

4.3.3 Procedural Steps of UIO Estimation

- 1) Construct augmented system
- 2) Solve LMI (4.60) to obtain P , Y and Z and then calculate the gains $K_1 = P^{-1}Y$; $N = P^{-1}Z$
- 3) Use N to solve H
- 4) Calculate other gains R , T and K_2
- 5) Obtain the augmented estimates by implemented UIO into the system.

4.4 Fault Tolerant Control Under Faults

The proposed methodology in this context is to control the wind turbine to achieve high efficiency with the existence of actuator faults. The objective of the proposed nonlinear adaptive controller is to achieve maximum power efficiency during partial load operation under additive faults. The faults types that could occur in the generator subsystem are bias and changed in dynamics such as high air content in the oil, hydraulic leak and pump wear.

There is available wind power energy denoted as P_w and there is power that can be extracted by the turbine P_a . Practically, it is impossible that any wind turbine can capture or extract all available power from wind. This is represented as $P_a = C_p(\lambda, \beta)P_w$ where C_p is power coefficient that indicates how much power can be extracted at a given tip speed ratio and pitch angle as shown in figure 22.

In the proposed fault tolerant scheme, an empirical equation for power coefficient was adopted as shown in Equation (4.60)

$$C_p(\lambda, \beta) = C_1 \left(\frac{C_2}{\lambda_i} - \right) C_3 \beta - C_4 \Big) e^{-C_5/\lambda_i} + C_6 \lambda \quad (4.60)$$

Where $\lambda_i = \frac{1}{\lambda + 0.08\beta} - \frac{0.035}{\beta^3 + 1}$, $C_1 = 0.5176$, $C_2 = 116$, $C_3 = 0.4$, $C_4 = 5$, $C_5 = 21$, $C_6 = 0.0068$

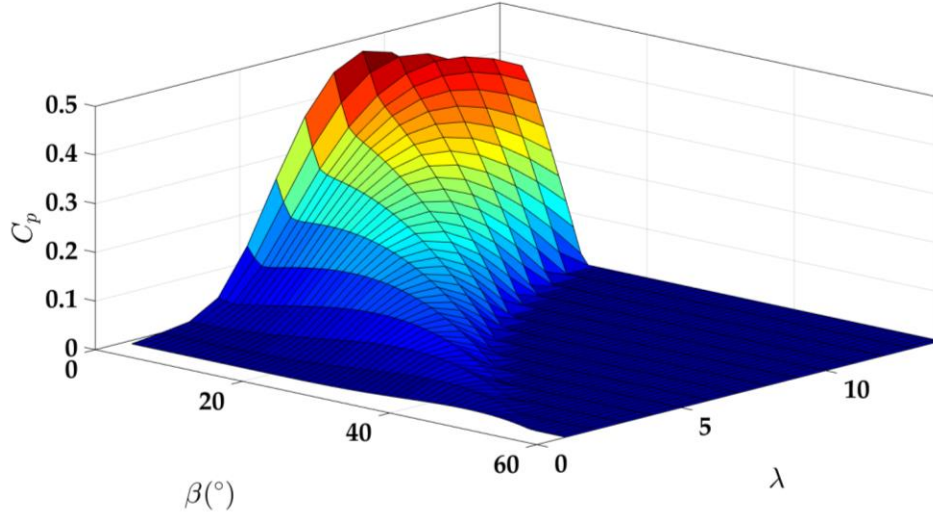


Figure 22: Power Coefficient Curves for Different Pitch Angles and Tip Speed Ratios

4.4.1 Objectives

The main objective is to design a fault tolerant control system that is capable to accommodate faults of wind turbine system during partial load operation without serious degradation of the system performance. The focused faults in this research is on the generator subsystem since wind turbine operating during partial load region will have a pitch reference equal to 0° . The target during partial load operation of wind turbine is to maintain the power coefficient at its maximum value to guarantee the maximum capture of energy. Figure 23 shows the maximum power coefficient is equal to 0.48 and found at pitch angle of 0° and at tip speed ratio of 8.1.

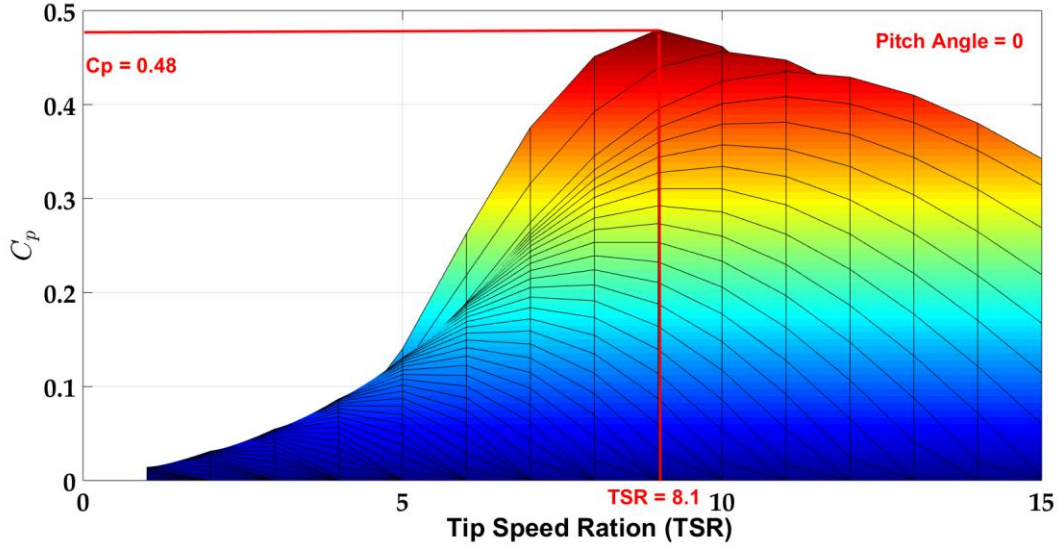


Figure 23: Power Coefficient Curves at Different Pitch Angles

4.4.2 Baseline Generator Torque Controller

The industrial baseline controller for the torque generator under partial load operation of wind turbine is formulated as follows:

$$\tau_{g,ref} = K\omega_g^2 \quad (4.61)$$

With $K = 0.5\rho A\eta_{dt}R^3C_{p,max}/N_g^3\lambda_{opt}^3$ and $C_{p,max} = 0.48$ and $\lambda_{opt} = 8.1$ while keeping the reference pitch angle at 0° to maximize the power extraction from available wind energy by maintaining maximum power coefficient. As a result, the dynamic equation for torque of the generator is modeled as:

$$\dot{\tau}_g = -a_g\tau_g + a_g\tau_{g,ref} \quad (4.62)$$

where $a_g = 1/d_g$ and d_g is a time delay.

4.4.3 Generator Torque Controller Under Faults

The baseline controller is to maintain the torque during partial load operation at optimal values of power coefficient and tip speed ratio since the pitch angle is fixed at zero. However, another objective is to maintain the maximum power during the partial load region under fault conditions since under fault conditions and disturbances the power coefficient and tip speed ratio will no longer be at their optimal values even though the pitch angle is kept at 0° . As a result, the torque of the generator will be controlled such that the error tracking dynamics ultimately reaches zero, as shown in Equation (4.61); where $\omega_{g,s}$ is the measured generator speed and $\omega_{g,d}$ is the desired generator speed.

$$e_g = \omega_{g,d} - \omega_{g,s} \quad (4.63)$$

This error dynamics is filtered or put into sliding surface S defined as:

$$S_g = c_g e_g + \dot{e}_g \quad (4.64)$$

Before we derive the time derivative of Equation (4.63), few concepts and reformulating the drive train equation to be able to take the time derivative of the filtered tracking error of rotor generator speed.

During wind turbine operation the generator speed and rotor speed are governed ideally by the drive train or gearbox ratio $\omega_g = N_g \omega_r$. Fault in the generator could harm the drive train system due to drive train torsional fatigue. So, the change of the drive train torsional angle would be required to be minimal to reduce the fatigue in the drive train subsystem. This implies that $\dot{\theta}_\Delta = 0$.

Therefore, the equations of the drive train are reformulated by considering the desired generator speed as shown in Equation (4.64)

$$\dot{\omega}_r = a_1\omega_r + a_2\omega_g + a_3\tau_r \quad (4.65)$$

$$\dot{\omega}_g = b_1\omega_r + b_2\omega_g + b_3\tau_g \quad (4.66)$$

where a_1, a_2, a_3, b_1, b_2 , and b_3 constant terms which are found from Equation (3.13) and (3.14). This would ease the formulation and derivation of the required equations. Also, the torque controller shall include the additive fault in the generator torque as shown in Equation (4.67)

$$\dot{\tau}_g = -a_g\tau_g + a_g\tau_{g,ref} + \Delta f_{GC} \quad (4.67)$$

where $\Delta f_{GC} = -a_g f_{Tg}$; and f_{Tg} denote to the bias or offset in the torque of the generator. It is worth to mention that the torque and its rate is limited as $\tau_{g_{min}} \leq \tau_g \leq \tau_{g_{max}}$ and $\dot{\tau}_{g_{min}} \leq \dot{\tau}_g \leq \dot{\tau}_{g_{max}}$.

Taking the time derivative of Equation (4.66) and considering Equation (4.67) results in:

$$\ddot{\omega}_g = q_1\omega_r + q_2\omega_g + q_3\tau_g + q_4\tau_r + q_5\tau_{g,r} - a_gb_3f_g \quad (4.68)$$

where $q_1 = b_2b_1 + a_3b_1$, $q_2 = b_2^2 + a_2b_1$, $q_3 = b_2b_3 - b_3a_g$, $q_4 = a_3b_1$ and $q_5 = a_gb_3$.

Now, the time derivative of the tracking filtered error of the generator speed shown in Equation (4.64) can be calculated as:

$$\dot{S}_g = c_g\dot{e}_g + \ddot{e}_g = g_d + g_1 - q_4\tau_r - q_5\tau_{g,r} + f_1 + d_1 \quad (4.69)$$

where $g_d = c_g\dot{\omega}_{g,d} + \ddot{\omega}_{g,d}$, $g_1 = k_1\omega_r + k_2\omega_g + k_3T_g$, $k_1 = -(c_1 + b_1c_g)$, $k_2 = -(c_2 + b_2c_g)$, $k_3 = -(c_3 + b_3c_g)$, $f_1 = b_3a_gf_g$ and $d_1 = k_1\nu_{\omega_r} + k_2\nu_{\omega_g} + k_3\nu_{\tau_{g,s}} - c_g\nu_{\dot{\omega}_g}$.

The desired generator speed $\omega_{g,d}$ can be found as:

$$\omega_{g,d} = \frac{N_g \lambda_{opt} V_r}{R} \quad (4.70)$$

However, there is physical limitation of the generator speed and its acceleration; thus Equation (4.70) expresses the upper limit of the generator speed in order to achieve maximum power production at optimal tip speed ratio. This upper limit or boundedness leads also that constant terms in Equation (4.69) to be bounded and specifically unknown bounds for f_1 and d_1 .

The designed torque controller for the generator is:

$$\tau_{g,r} = \frac{1}{q_5} \left(g_1 - q_4 \tau_r + \hat{f}_1 + \hat{d}_1 \tanh \left(\frac{S_g}{\eta_{d_1}} \right) + g_{d,max} \tanh \left(\frac{S_g g_{d,max}}{\eta_{g_d}} \right) + k_2 S_g \right) \quad (4.71)$$

where $\hat{d}_1$, and $\hat{f}_1$ are the estimates of d_1 and f_1 and k_2 , η_{d_1} and η_{g_d} are positive parameters that shall be selected to achieve the objective of the fault tolerant controller. Also, adaptation laws are selected as

$$\dot{\hat{f}}_1 = S_g - \sigma_{f_1} \hat{f}_1$$

$$\dot{\hat{d}}_1 = S_g \tanh \left(\frac{S_g}{\eta_{d_1}} \right) - \sigma_{d_1} \hat{d}_1 \quad (4.72)$$

$$\dot{\hat{\rho}}_{\tilde{f}_1} = -\sigma_{\tilde{f}_1} \hat{\rho}_{\tilde{f}_1}$$

The following lemmas are used to prove the boundedness of the designed controller and adaptation laws in Equation (4.71) and (4.72); respectively.

Lemma 1: for a selected positive definite Lyapunov function $V(x, t)$ and satisfies $\dot{V} < -E_1 V + E_2$ where E_1 and E_2 are positive constants, then the solution is uniformly ultimately bounded for bounded initial conditions

Lemma 2: if $\tilde{a} = \hat{a} - a$, then for any $\sigma > 0$ the following holds $-2\sigma\tilde{a}\hat{a} \leq -\sigma\tilde{a}^2 + \sigma a^2$ such that $(\tilde{a} + a)^2 \geq 0$

Lemma 3: for any variable Ω and $\eta > 0$, then $0 < |\Omega| - \Omega \tanh\left(\frac{\Omega}{\eta}\right) < \mathcal{K}_p$ where $\mathcal{K}_p$ is a constant that satisfies $\mathcal{K}_p = e^{-\mathcal{K}_p-1}$ which is numerically $\mathcal{K}_p = 0.2785$

Proof: to prove the effectiveness of the torque controller formulated in Equation (4.70) with its adaptation laws in Equation (4.72) along with the Lemmas provided, a candidate Lyapunov function is designed as follows:

$$V = \frac{1}{2}S_g^2 + \frac{1}{2}\tilde{d}_1^2 + \frac{1}{2}\tilde{f}_1^2 + \frac{1}{2}\tilde{\rho}_{f_1}^2 \quad (4.73)$$

where $\tilde{f}_1 = \hat{f}_1 - f_1$, $\tilde{d}_1 = \hat{d}_1 - d_1$,

Taking the time derivative of V_g yields to:

$$\dot{V} = S_g\dot{S}_g + \tilde{d}_1\dot{\tilde{d}}_1 + \tilde{f}_1\dot{\tilde{f}}_1 + \tilde{\rho}_{f_1}\dot{\tilde{\rho}}_{f_1}$$

$$\dot{V} = \dot{V}_1 + \dot{V}_2 + \dot{V}_3 + \dot{V}_4 - k_2S_g^2$$

where

$$\dot{V}_1 = S_g\dot{f}_1 - S_g\dot{\hat{f}}_1 + S_g\dot{\tilde{f}}_1 - \sigma_{f_1}\hat{f}_1\tilde{f}_1 - \tilde{f}_1\dot{\tilde{f}}_1$$

$$\dot{V}_2 = S_g\dot{d}_1 - S_g\dot{q}_4 + S_g\dot{\tilde{d}}_1 \tanh\left(\frac{S_g}{\eta_{d_1}}\right) - S_g\dot{\hat{d}}_1 \tanh\left(\frac{S_g}{\eta_{d_1}}\right) - \sigma_{d_1}\hat{d}_1\tilde{d}_1$$

$$\dot{V}_3 = S_g\dot{g}_d - S_g\dot{g}_{d,max} \tanh\left(\frac{S_g g_{d,max}}{\eta_{g_d}}\right)$$

$$\dot{V}_4 = -\sigma_{\tilde{f}_1} \hat{\rho}_{\tilde{f}_1} \tilde{\rho}_{\tilde{f}_1}$$

Using Lemma 1 and 2:

$$\begin{aligned}\dot{V}_1 &< -\frac{\sigma_{f_1}}{2} \tilde{f}_1^2 + \frac{\sigma_{f_1}}{2} \bar{f}_1^2 + \rho_{\tilde{f}_1} \rho_{\dot{f}_1} \\ \dot{V}_2 &\leq D \left(|s_{\omega_g}| - S_g \tanh\left(\frac{S_g}{\eta_{d_1}}\right) \right) - \frac{\sigma_{d_1}}{2} \tilde{d}_1^2 + \frac{\sigma_{d_1}}{2} D^2 < D \mathcal{K}_p \eta_{d_1} - \frac{\sigma_{d_1}}{2} \tilde{d}_1^2 + \frac{\sigma_{d_1}}{2} D^2 \\ \dot{V}_3 &< \mathcal{K}_p \eta_{g_d} \\ \dot{V}_4 &\leq \frac{\sigma_{\tilde{f}_2}}{2} \rho_{\tilde{f}_2}^2 - \frac{\sigma_{\tilde{f}_2}}{2} \tilde{\rho}_{\tilde{f}_2}^2\end{aligned}$$

From Lemma 3, we have

$$E_1 = \min(2k_2, \sigma_{d_1}, \sigma_{f_1}, \sigma_{\tilde{f}_1}) > 0$$

$$E_2 = Dk_p \eta_{d_2} + k_p \eta_{g_d} + \sigma_{d_2} D^2/2 + \sigma_{\tilde{f}_2} \rho_{\tilde{f}_2}^2/2 + \sigma_{f_2} \bar{f}_2^2/2 + \rho_{\tilde{f}_2} \rho_{\dot{f}_2} > 0$$

This concludes the uniformly ultimately bounded system.

Now, by using the estimated fault $\hat{f}_1$ instead of f_1 in Equation (4.68) the fault on the generator can be estimated by

$$\hat{f}_g = \frac{\hat{f}_1}{b_3 a_g} \tag{4.74}$$

CHAPTER 5

Simulations and Results

5.1 Introduction

In this Chapter, simulations are done using MATLAB/SIMULINK Software based on the developed work shown in detail in Chapter 4. In section 5.2 and 5.3, various estimation techniques are implemented to estimate aerodynamic torque and torque coefficient; respectively including their tracking errors as performance index.

In section 5.4, simulation was done to simultaneously estimate the states and faults of the augmented system of wind turbine using UIO.

In section 5.5, a baseline controller was simulated during partial load operation for fault free case and fault conditions. Similarly, adaptive fault tolerant controller is simulated for the same region and same cases for baseline controller. A comparative analysis is done between two techniques against performance indices.

5.2 Direct Estimation of Aerodynamic Torque

Figure 24 shows the wind speed profile that mimics the behavior of real wind speed profile. However, the wind speed profile used in the simulation ranges from 0-2200 seconds instead of 0-4400 seconds for faster simulation time since the sampling time is 0.01 seconds.

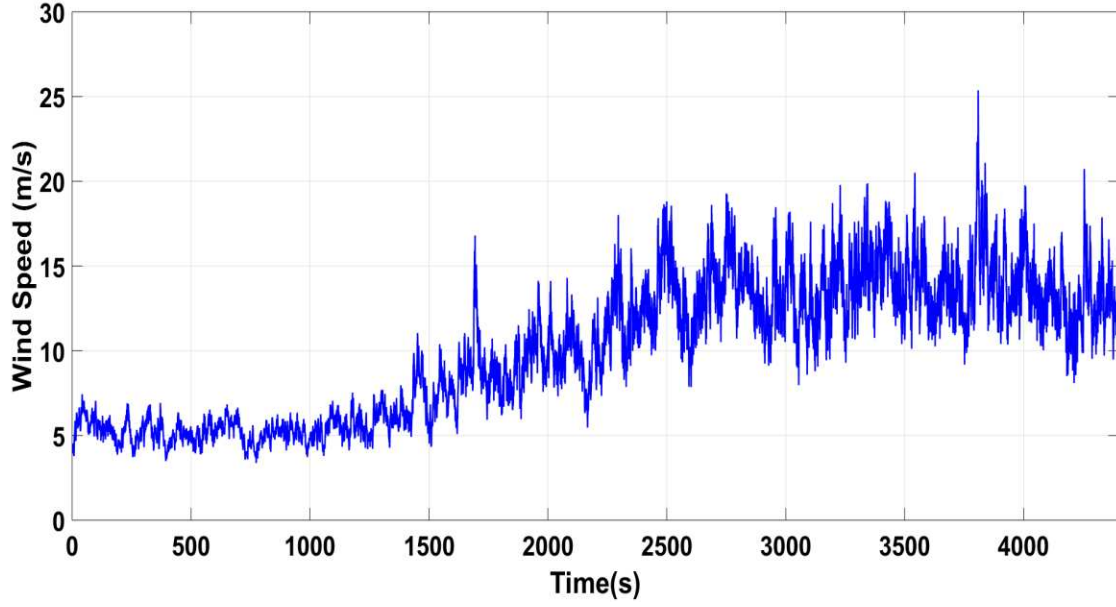


Figure 24: Wind Speed Profile

In this section, the aerodynamic torque Equation (3.8) is directly estimated using four techniques. First, T-S fuzzy based estimation using Equations (4.2 to 4.5). Second, RLS-FF based estimation using Equations (4.6,4.7,4.10 & 4.11). Third, RLS-KF based estimation using Equations (4.6,4.7,4.13 & 4.14). Forth, RLS-NG based estimation using Equations (4.6, 4.7, 4.11 & 4.20). Same equations are used to estimated torque coefficient which is presented in next section. The parameters involved in the estimation process are wind speed v_w and rotor angular speed w_r .

5.2.1 T-S Fuzzy Based Estimation

Figure 25 shows the aerodynamic estimation using T-S fuzzy based scheme along with absolute error. The T-S fuzzy Equations used are (4.2-4.5), and its parameters are $W_1 = 0.0591, W_2 = 2.5, N_1 = -2, N_2 = 5, N_3 = 35, N_4 = 70, V_1 = 1, V_2 = 13, V_3 = 13$ which represents the set of local operation modes using the designed membership functions

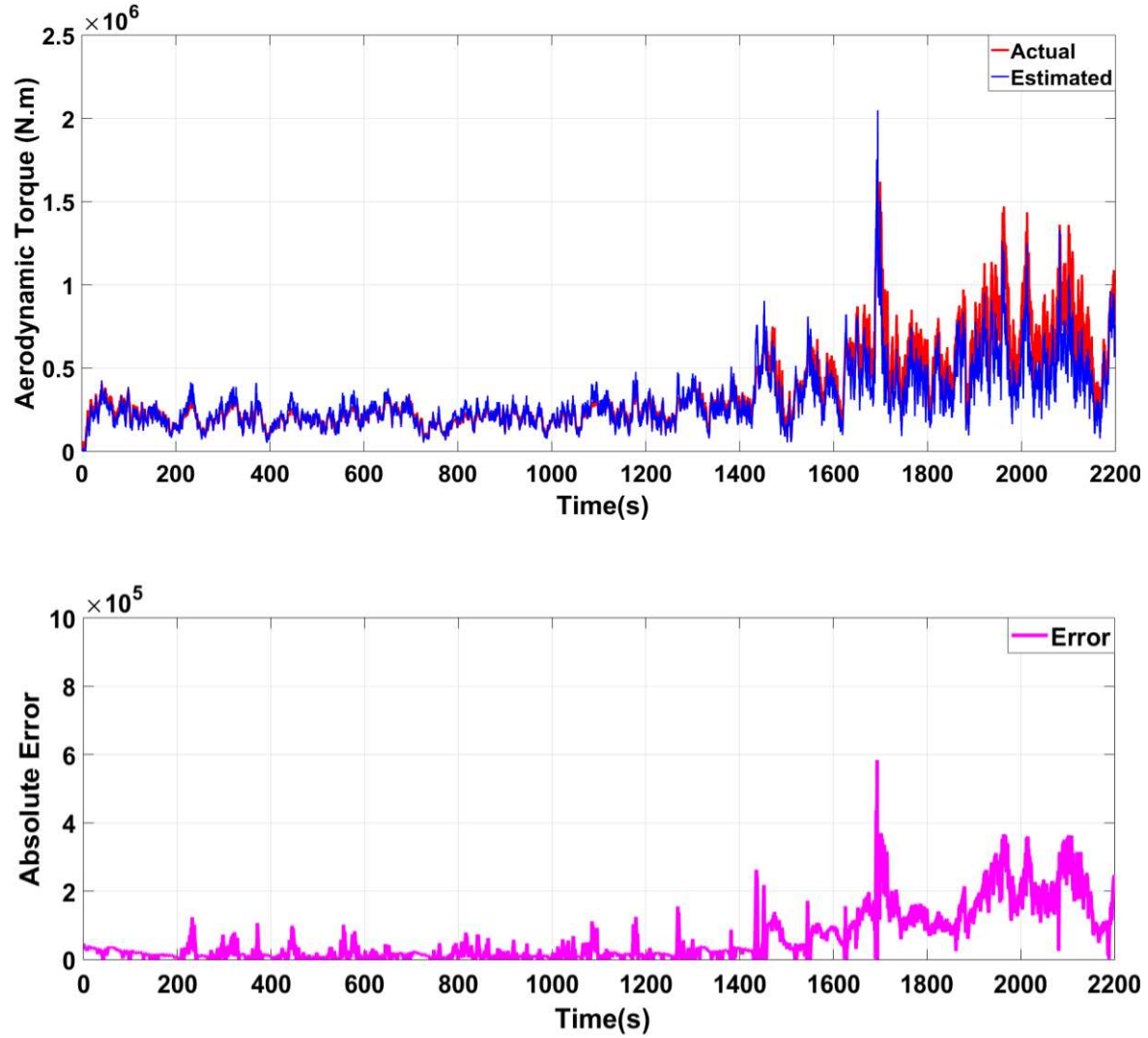


Figure 25: T-S Fuzzy Modeling for Aerodynamic Torque Estimation with Absolute Error

The results show that there is sort of tracking the aerodynamic torque with fluctuations but error and fluctuation increases as aerodynamic torque increases. This is considered as a shortcoming of using this technique for estimation purposes. The maximum absolute error reached around 36% at time of 1700 s in the simulation as shown in Figure 25.

5.2.2 RLS-FF Based Estimation

Figure 26 shows the aerodynamic estimation using RLS-FF based estimation along with absolute error. The RLS-FF approach used Equations ((4.6,4.7,4.10 & 4.11) and its forgetting factor $\lambda(t)$ was set to 1 and initial parameters covariance $P(t)$ was set to 100.

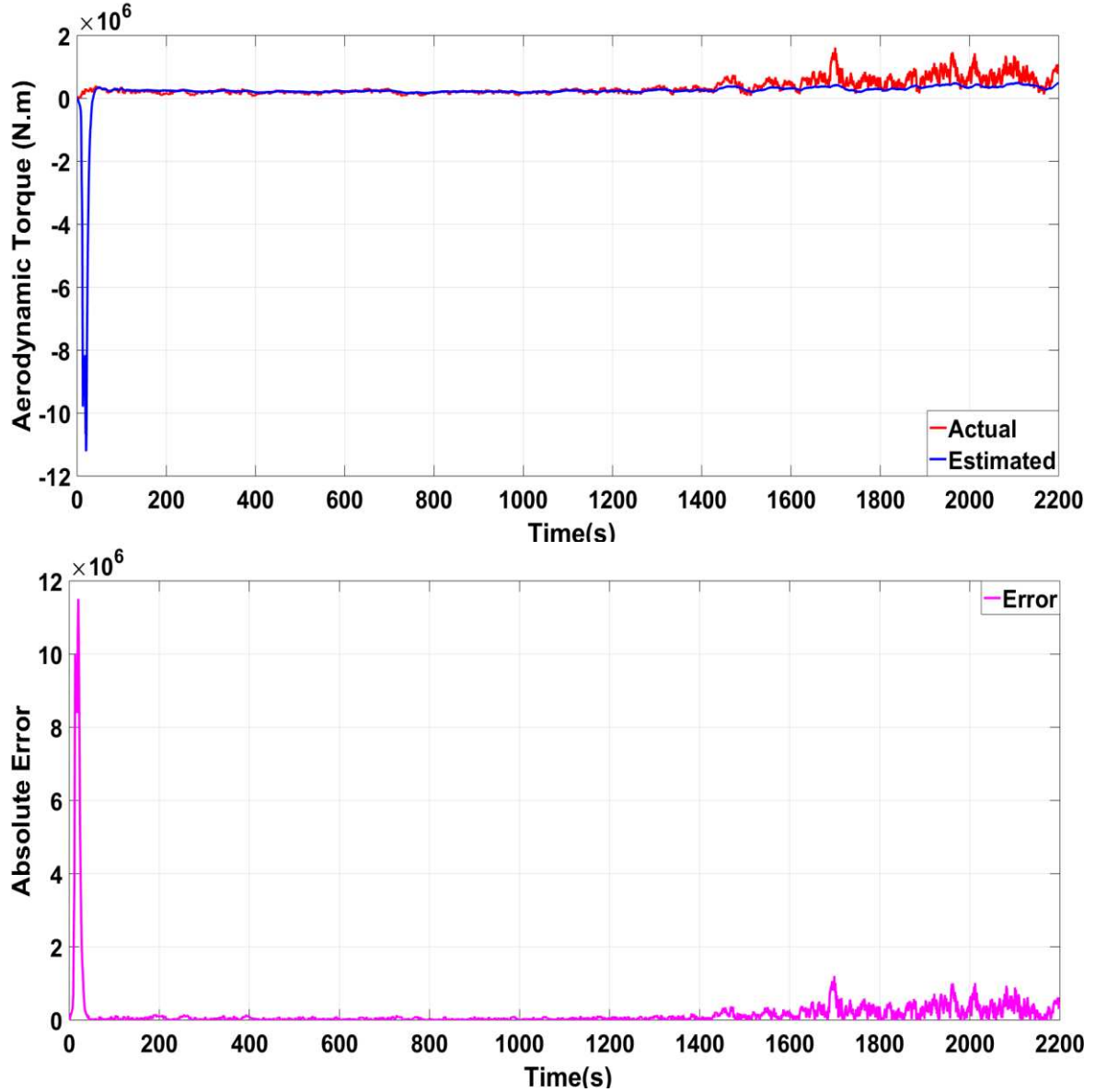


Figure 26: RLS-FF for Aerodynamic Torque Estimation with Absolute Error

For clarity, Figure 26 is enlarged to show the performance of the algorithm in estimating the aerodynamic torque and shown in Figure 27. It showed clearly the high initial error; however, large error was persisting during the simulation. Despite the high initial error, the maximum obsolete error in percent reached around 75% at simulation time 1700 s.

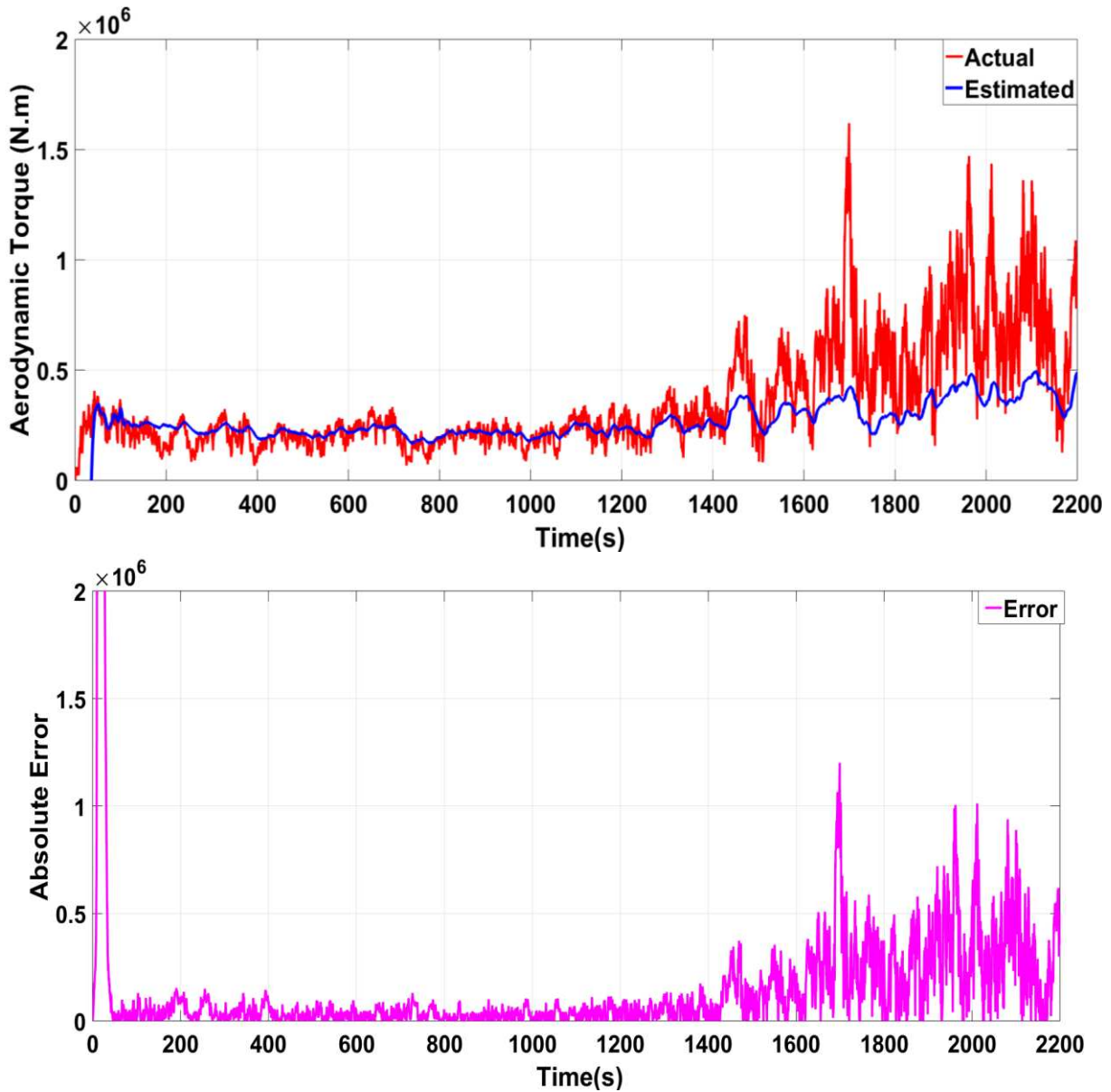


Figure 27: RLS-FF for Aerodynamic Estimation Enlarged for Clarity

5.2.3 RLS-KF Based Estimation

RLS-KF based estimation used Equations (4.6,4.7,4.13 & 4.14) with assumption that residuals are white noise and their variance is equal to one and its main parameters namely the process noise covariance was set to 1 and parameter noise covariance was set to 100. RLS-KF based estimation technique was showing very promising results except high initial jump but then quickly converge to the actual value as shown in Figure 28. The maximum absolute error in percent reached about 2% at simulation time of 2000s.

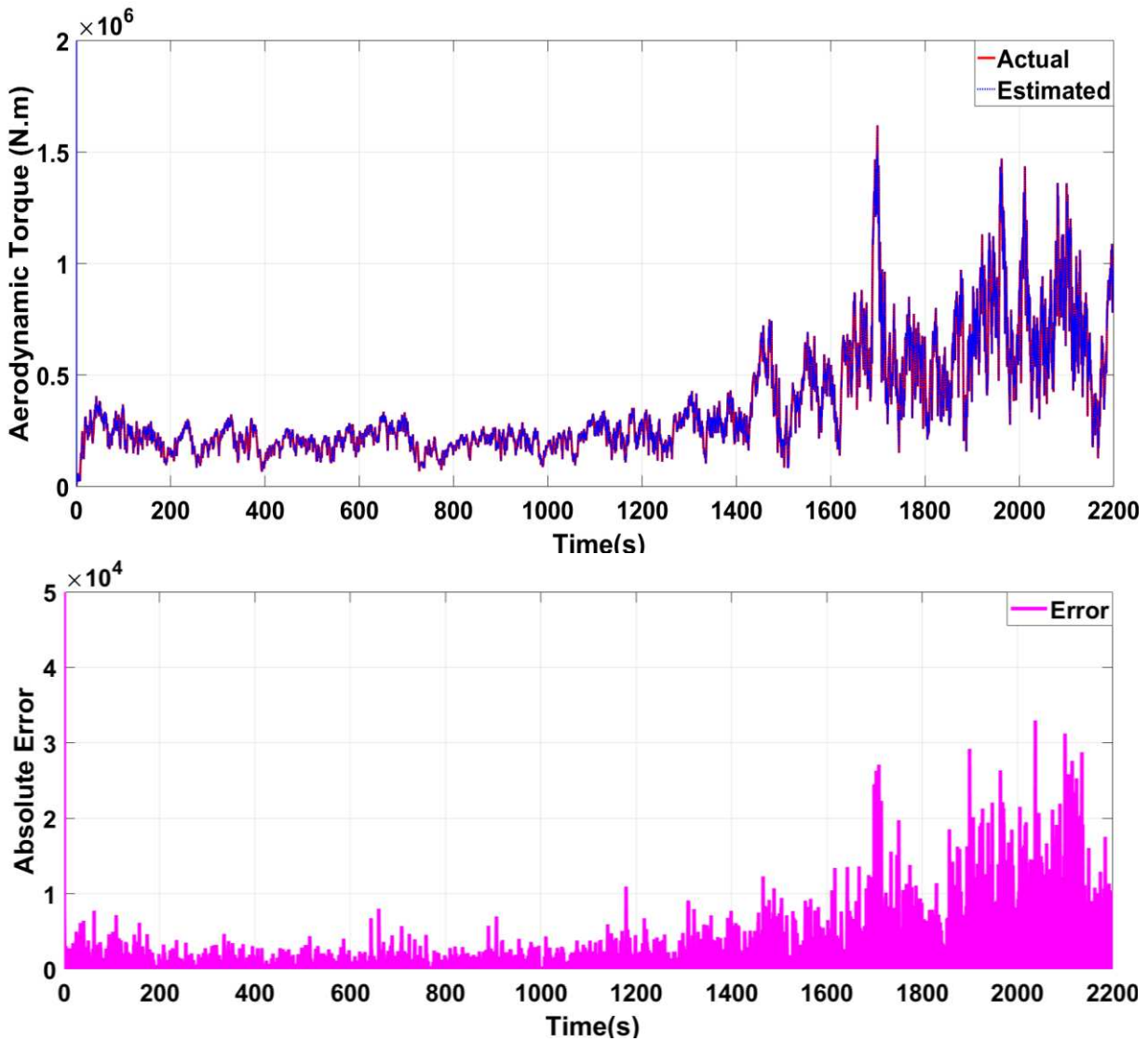


Figure 28: RLS-KF Aerodynamic Torque Estimation

5.2.4 RLS-NG Based Estimation

RLS-NG based estimation algorithm used Equations (4.6, 4.7, 4.11 & 4.20) and its parameters Bias was set to $2.2204\text{e-}16$ and adaptation gain γ was set to 1. This algorithm performed also very well with less initial jumps compared with RLS-KF technique as shown in Figure 29. The maximum absolute error in percent was around 2% at simulation time of around 2000s.

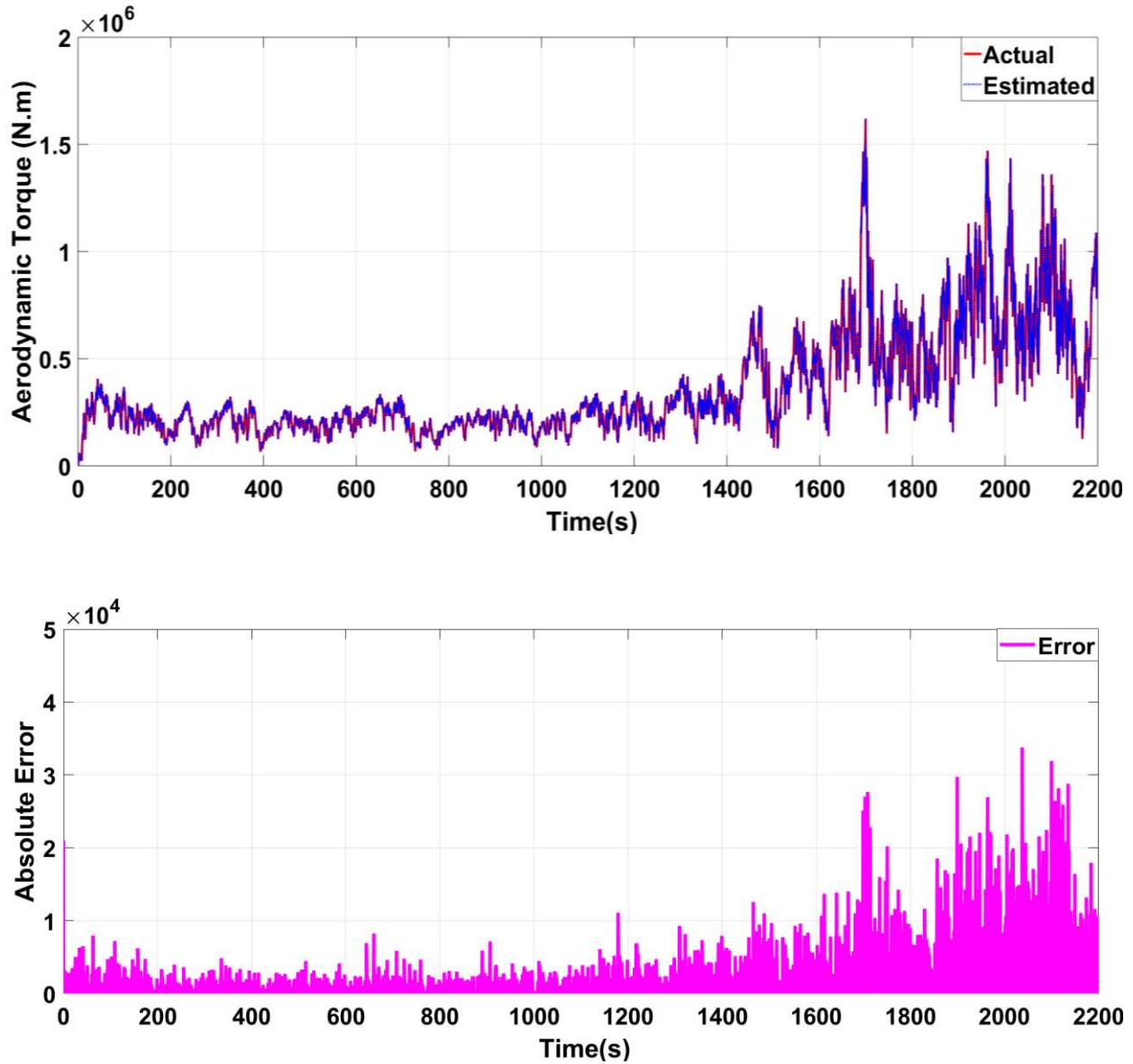


Figure 29: RLS-NG Aerodynamic Torque Estimation

5.3 Estimation of Torque Coefficient

The below figures show the simulation results for implementing the same estimation techniques presented in the previous section to estimate the aerodynamic torque. However, in this section, torque coefficient is first estimated using same techniques and equations with same parameters but to estimate the lookup table defined by the torque coefficient and then aerodynamic torque is calculated accordingly using Equation (3.8)

5.3.1 T-S Fuzzy Based Estimation

This approach showed high jumps initially with relatively large in the absolute error magnitude between estimated and actual values as shown in Figure 30.

Then, aerodynamic torque was calculated as shown in Figure 31. The aerodynamic torque experienced high initial jump in the estimated value then it started to converge and it was indicating that the value was irresponsive to high fluctuations but appeared with offset compared with the actual aerodynamic torque.

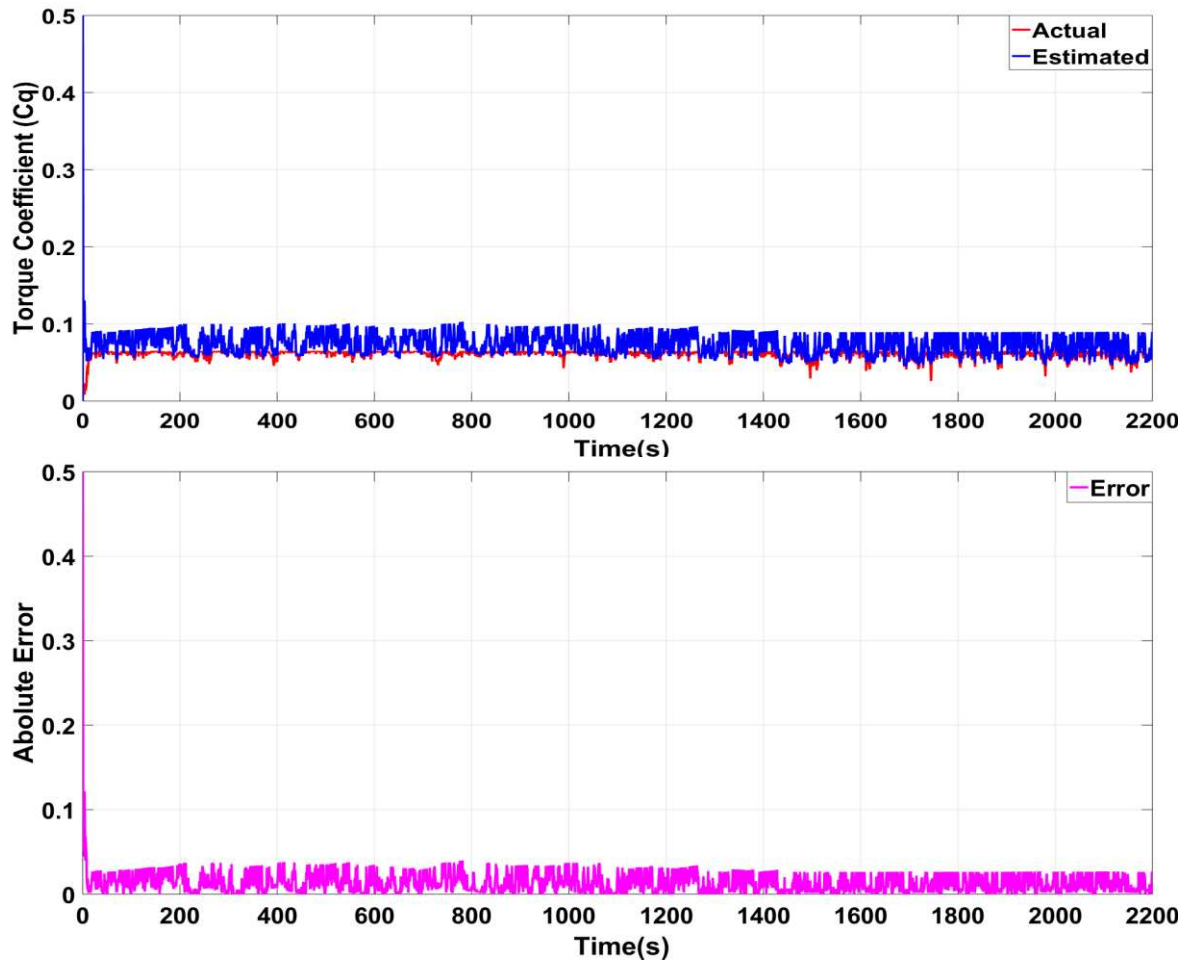


Figure 30: T-S Fuzzy Torque Coefficient Estimation

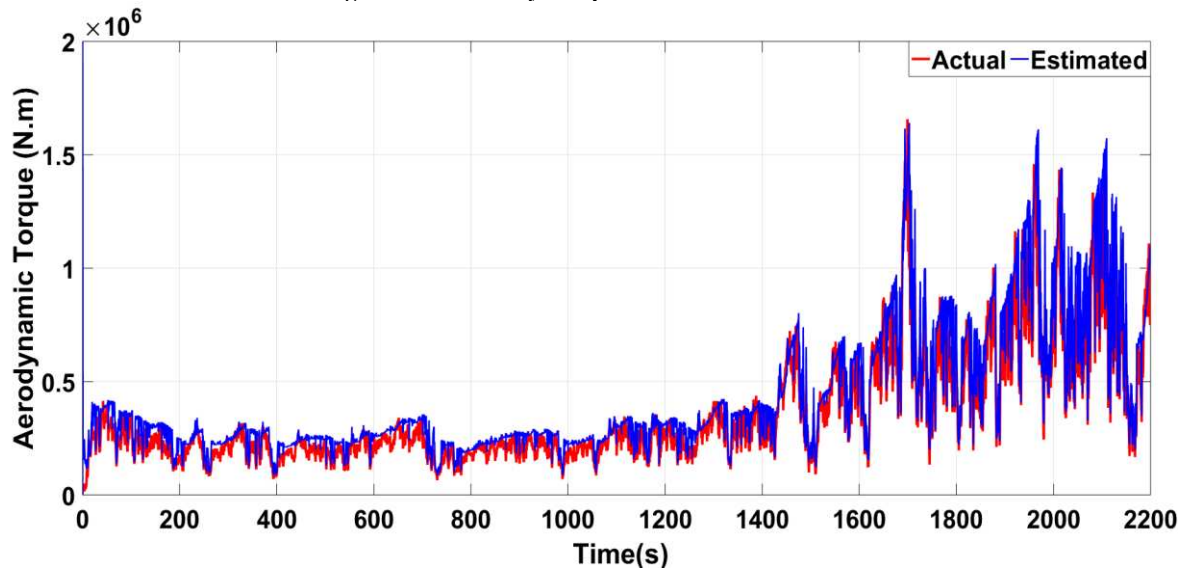


Figure 31: T-S Fuzzy Aerodynamic Output after Coefficient Estimation

5.3.2 RLS-FF Based Estimation

This approach showed high jumps initially with relatively large in the absolute error between estimated and actual values as shown in Figure 32 and the aerodynamic torque is calculated as shown in Figure 33.

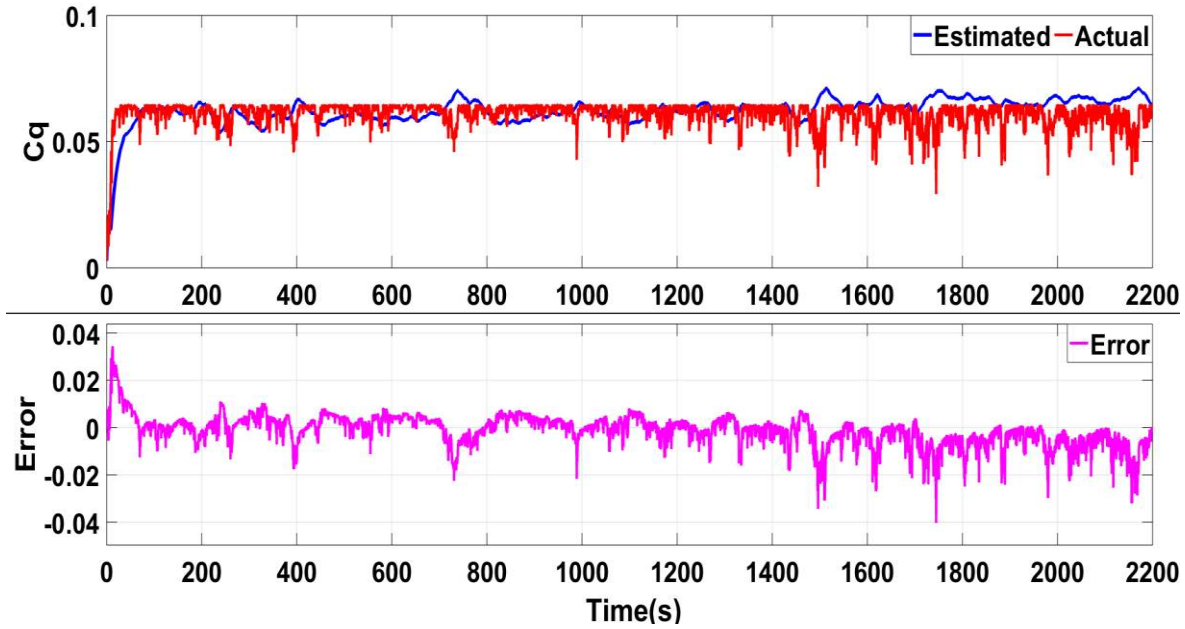


Figure 32: RLS-FF Torque Coefficient Estimation

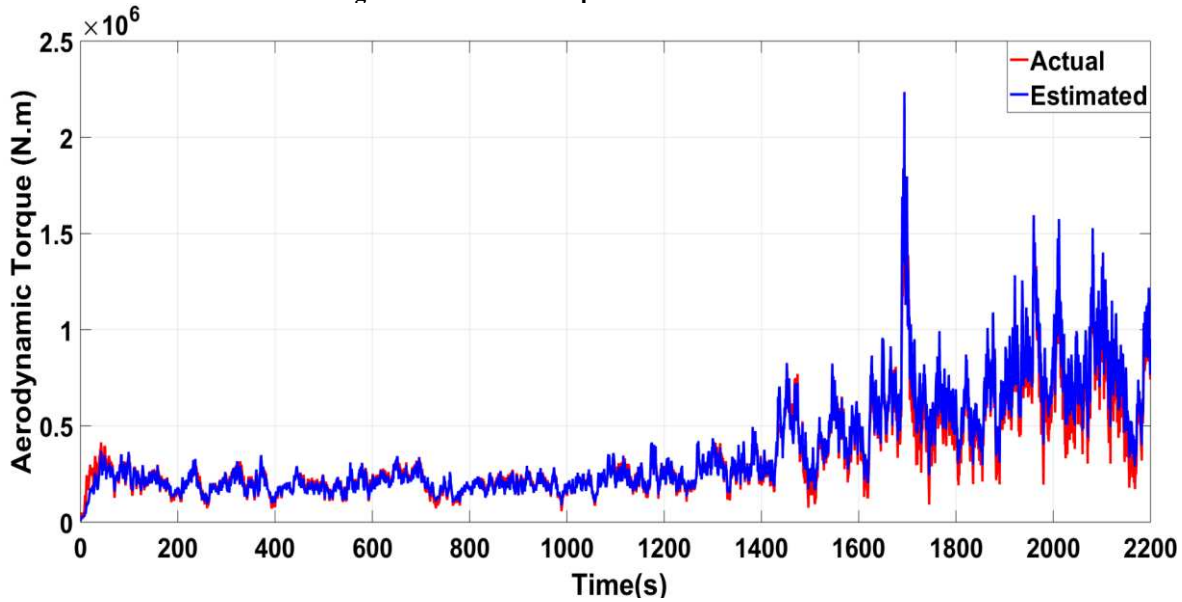


Figure 33: RLS-FF Aerodynamic Torque after Coefficient Estimation

5.3.3 RLS-KF Based Estimation

This approach showed better results in terms of error magnitude between estimated and actual values as shown in Figure 34 and then aerodynamic torque was calculated as shown in Figure 35. Results showed the high performance of this approach in estimating the aerodynamic torque with very small error; however, there is high initial jump of the calculated aerodynamic torque.

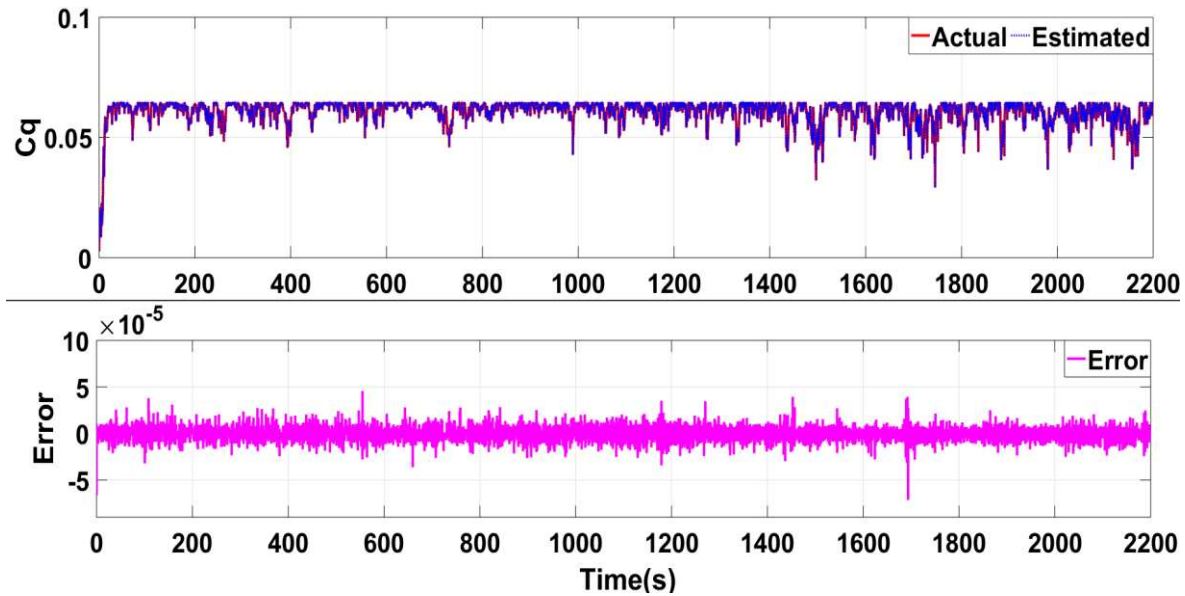


Figure 34: RLS-KF Torque Coefficient Estimation

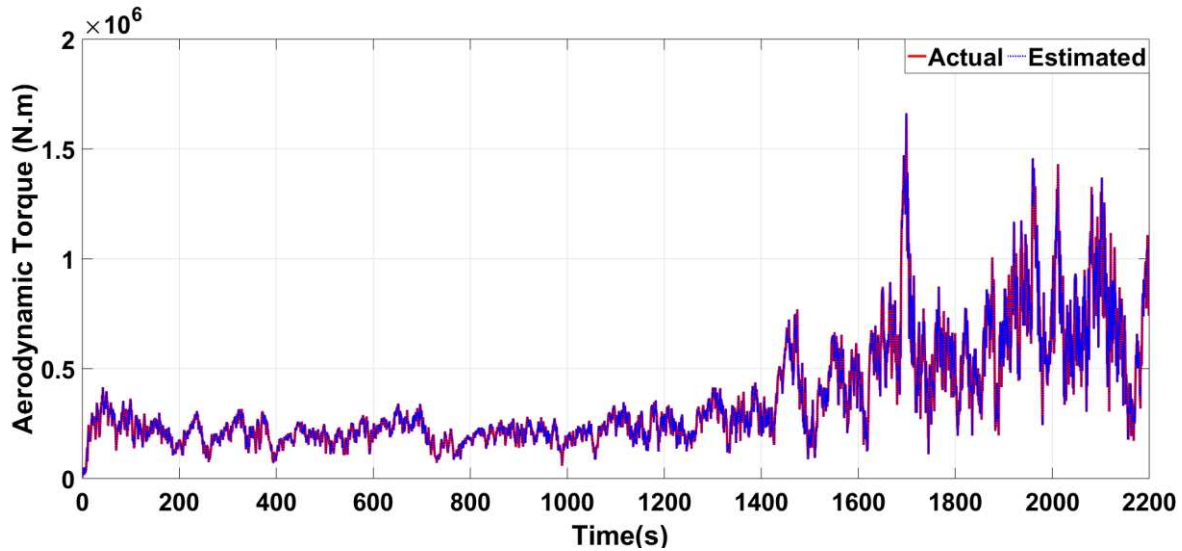


Figure 35: RLS-KF Aerodynamic Torque after Coefficient Estimation

5.3.4 RLS-NG Based Estimation

This approach showed high jump initially with relatively large in the error between estimated and actual values but then error converges as shown in Figure 36 and then aerodynamic torque was calculated as shown in Figure 37. This approach also proves its high performance in estimation despite the high initial jump in the calculated aerodynamic torque.

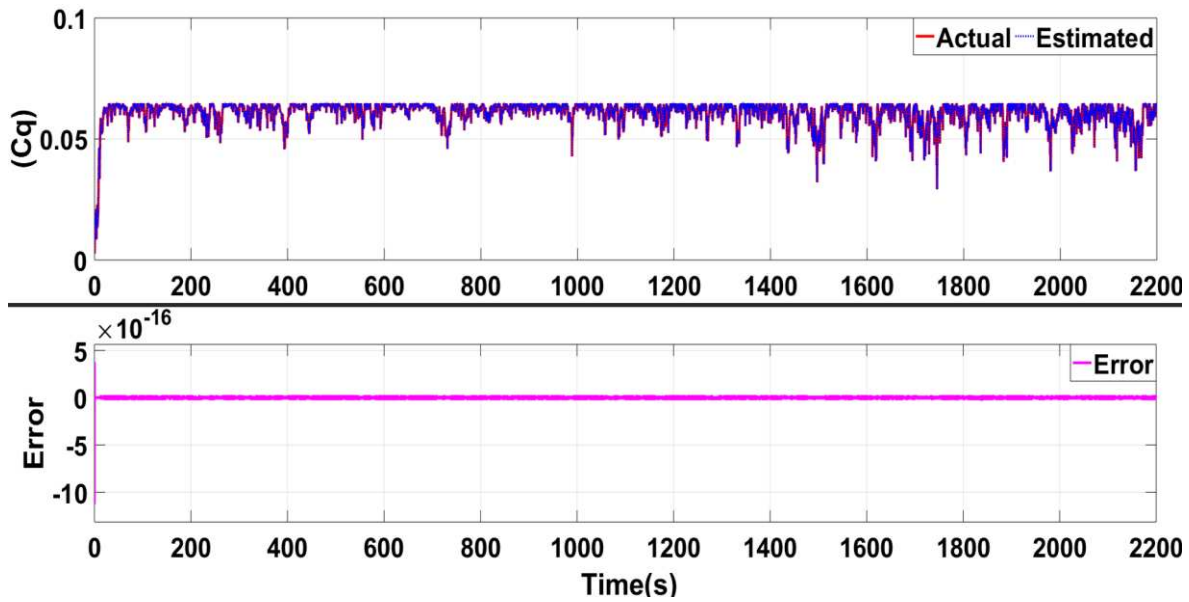


Figure 36: RLS-NG Torque Coefficient Estimation

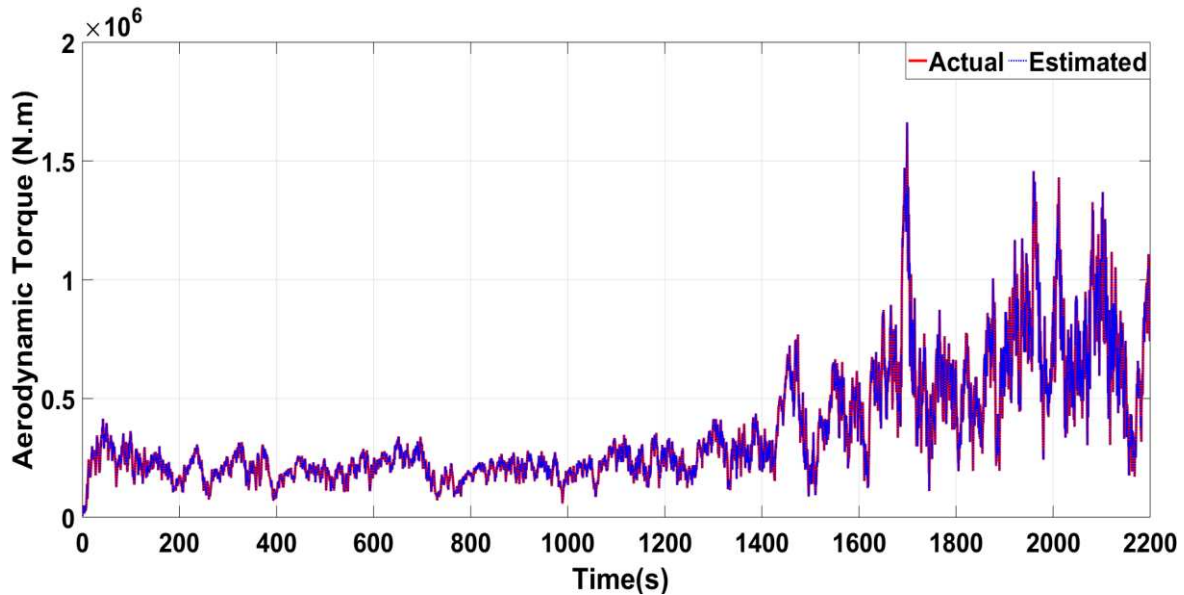


Figure 37: RLS-NG Aerodynamic Torque after Coefficient Estimation

In summary, two scenarios were implemented to estimate the aerodynamic torque of wind turbine rotor during partial load operation of wind turbine. First approach was to estimate aerodynamic torque directly. Second approach was to estimate torque coefficient then aerodynamic torque was calculated by the governed equation. Both approaches were using the same estimation techniques and same parameters for better comparison. Comparing both aerodynamic torque values, results showed that torque coefficient estimation was giving better results as it requires to estimate the nonlinear look-up table only while second approach was to estimate the aerodynamic torque value without intermediate estimate. Overall, RLS-KF and RLS-NG showed good results in both approaches. However, as T-S fuzzy based showed potential to perform better, optimizing the parameters generally for T-S fuzzy based techniques and RLS-FF could improve their performance. |

5.4 Fault Tolerant Control Under Faults

In this section, a comparison between baseline controller and adaptive fault tolerant controller is presented for both fault-free case and fault-case. Their results were measured against performance indices related to power efficiency and rate of change of drive train torsion angle. For each subsection, four simulation figures are presented in sequence: power coefficient, tip speed ratio, actual power and change of rate for drive train torsion angle. In this arrangement, it gives a clear picture of the differences between both schemes and make the analysis easy to conclude the results. It is worth to mention that all simulation figures are produced for only partial load operation of wind turbine.

5.4.1 Baseline Controller Without Faults

Figure 38 shows the actual power coefficient vs optimal power coefficient for baseline controller in fault-free case. The result shows good tracking of the optimal power coefficient.

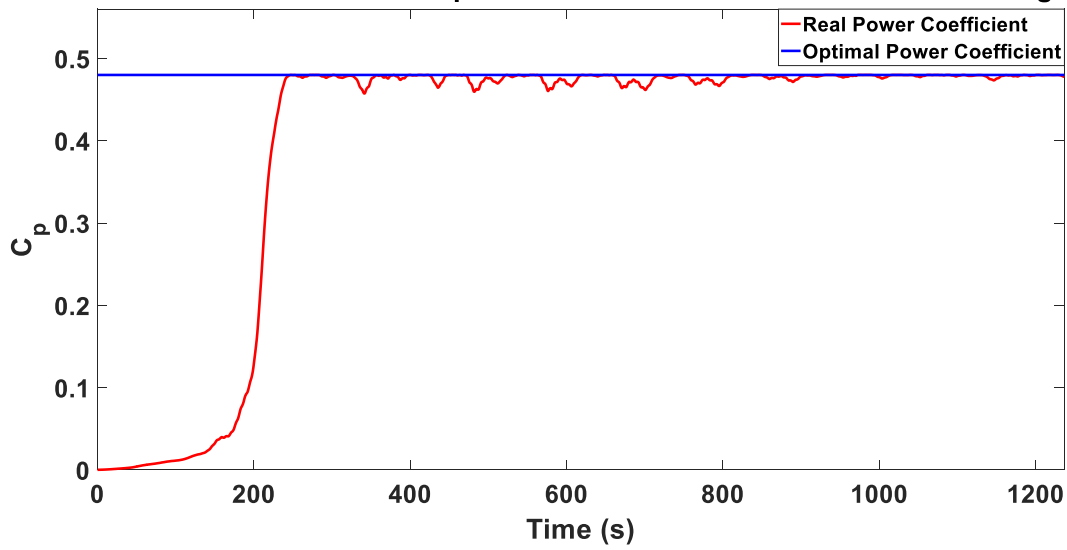


Figure 38: Actual vs Optimal Power Coefficient for Baseline Controller Without Faults

Figure 39 shows the actual tip speed ratio vs the optimal tip speed ratio for baseline controller in the fault-free case. Since it depends on rotor angular speed and wind speed it is highly expected to have fluctuations and offset from the optimal tip speed ratio.

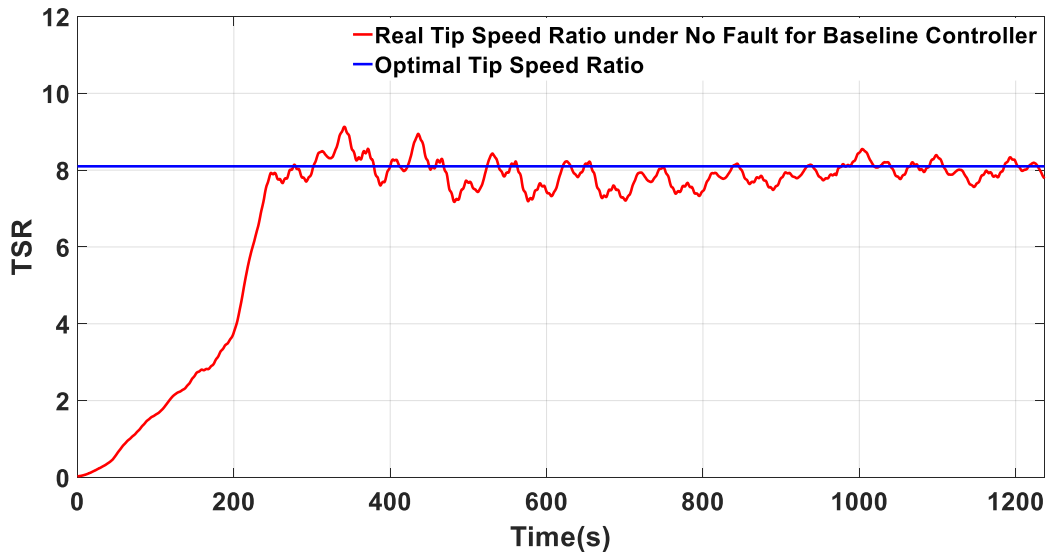


Figure 39: Actual vs Optimal Tip Speed Ratio for Baseline Controller Without Faults

Figure 40 shows the optimal power vs the actual power produced using a baseline controller in the fault-free case. The result shows fair tracking of the optimal power with offset.

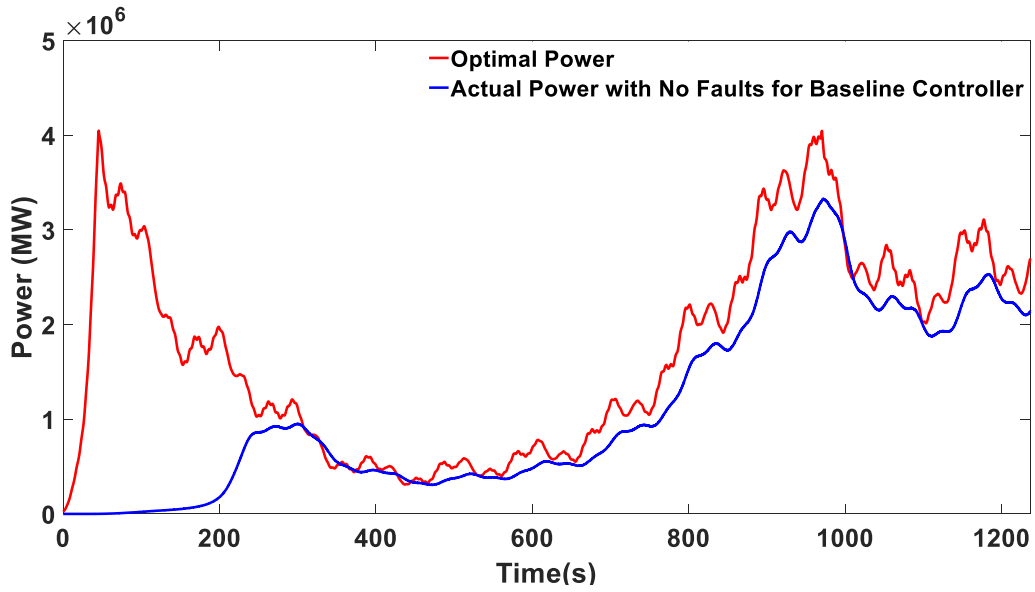


Figure 40: Actual vs Optimal Power for Baseline Controller Without Faults

Figure 41 shows the torsion angle of drive train subsystem using a baseline controller in the fault-free case. This represent the stress on the drivetrain subsystem of the wind turbine system.

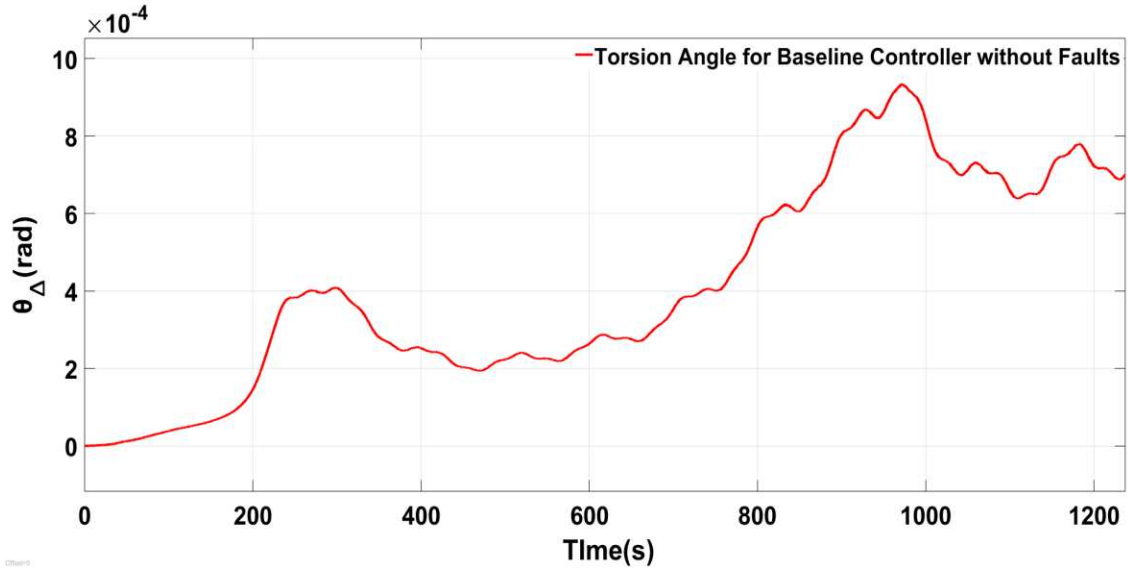


Figure 41: Torsion Angle of Drive Train Subsystem for Baseline Controller Without Faults

5.4.2 Baseline Controller with Faults

Figure 42 shows case# 1 of generator faults which is an offset or bias of 2000 N.m during period of 300-500s and by an offset of 5000 N.m during periods of 700s and 900s.

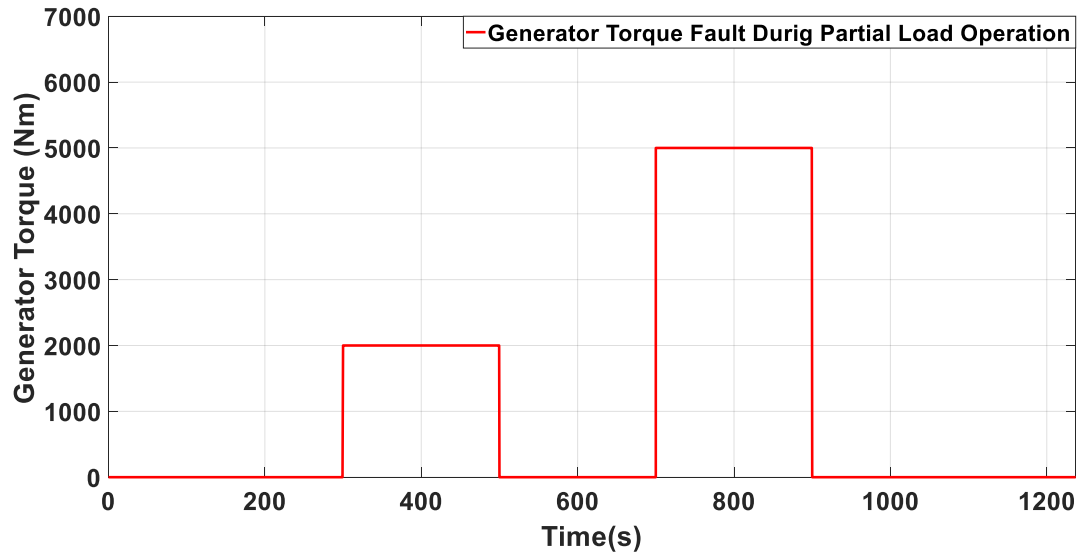


Figure 42: Designed Additive Fault in The Torque of The Generator (Case# 1)

Figure 43 shows case# 2 of the pitch bias fault by 10 degrees during the period of 900-1100s.

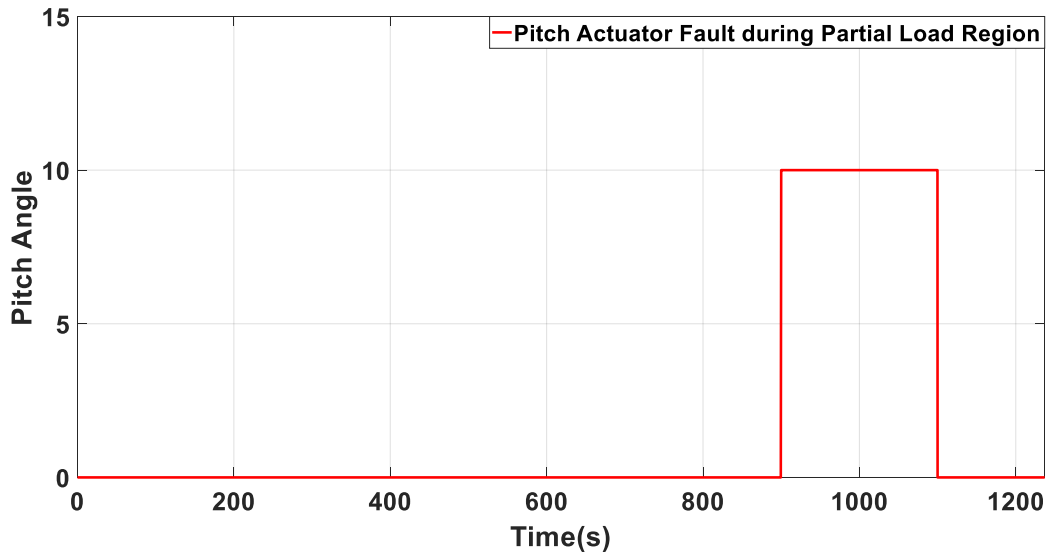


Figure 43: Designed Additive Pitch Angle Fault (Case # 2)

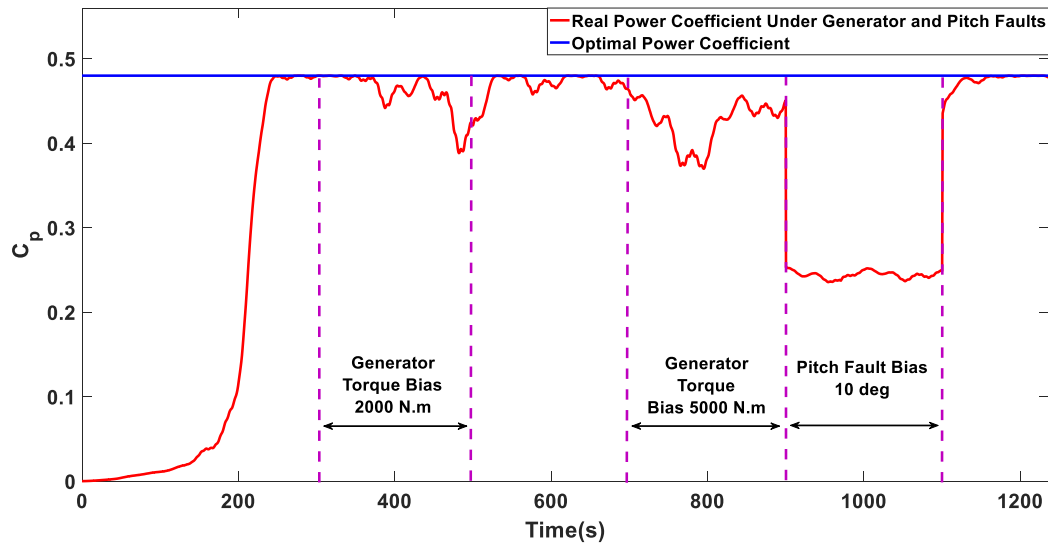


Figure 44: Effect of Case# 1 & 2 Faults in The Power Coefficient Using Baseline Controller

In this research, the focus is on the partial load operation and pitch angle reference is always 0 to maximize the power extraction. Therefore, an adaptive fault tolerant control scheme is implemented to deal with only generator faults. Figure 44 shows the effect of case#1 and case# 2 faults in the power coefficient using baseline controller while Figure 45 shows the effect of case#1

and case#2 faults in the tip speed ratio using baseline controller. It is clear that the tip speed ratio was affected due the faults occurred in the system.

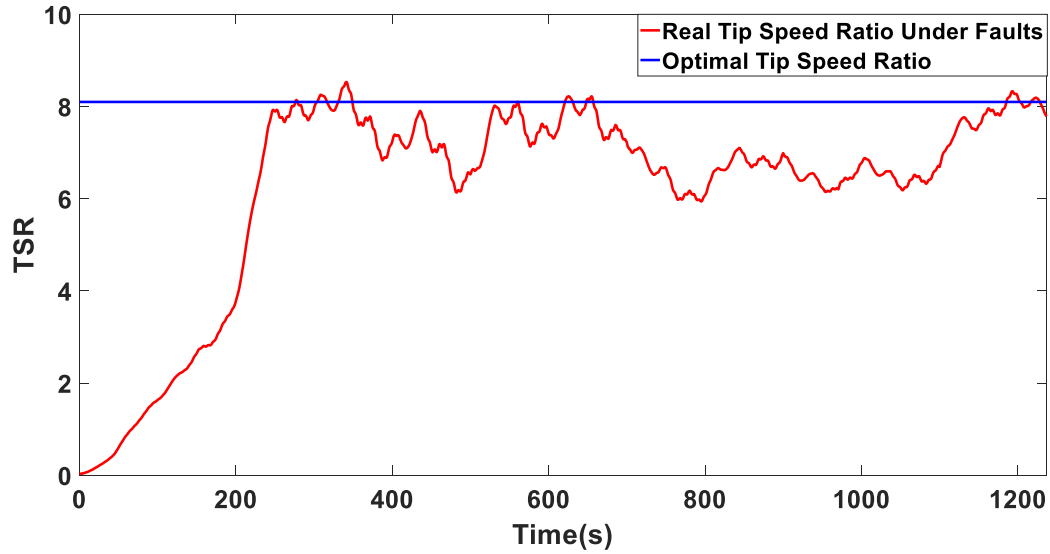


Figure 45: Effect of Case# 1 and 2 Faults in Tip Speed Ratio Using Baseline Controller

Figure 46 shows the actual power generated effected by case#1 and case#2 faults using baseline controller. The results showed clear degradation of the generated power compared with the optimal power.

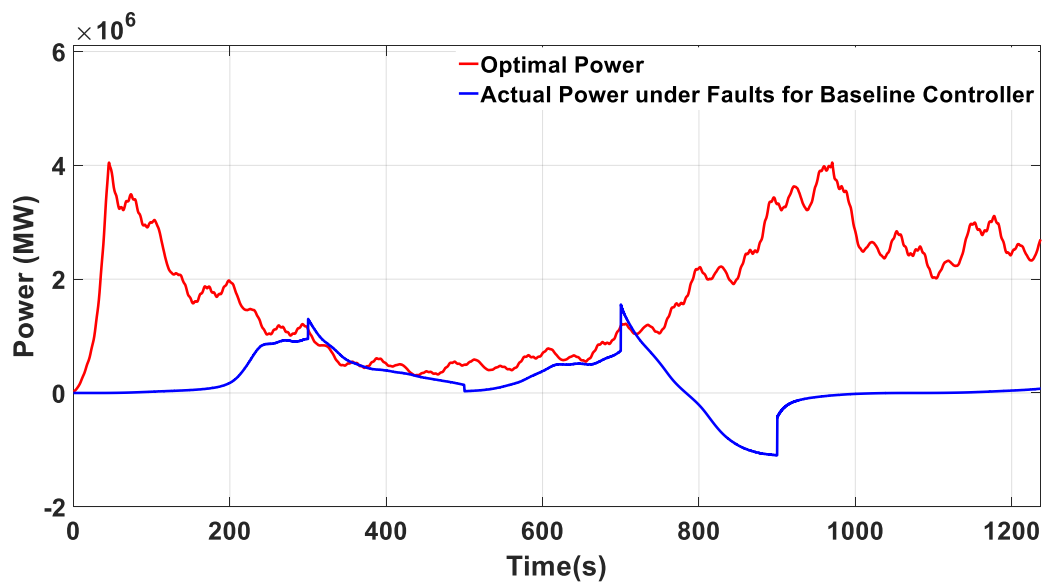


Figure 46: Effect of Case# 1 and 2 Faults in Actual Power Using Baseline Controller

Figure 47 shows the effect of case#1 and case#2 faults in the rate of change of drive train torsion angle using baseline controller. The figure shows that the drive train subsystem experienced high rate of change of torsion angle which is indicated by the oscillatory fluctuations especially during fault periods.

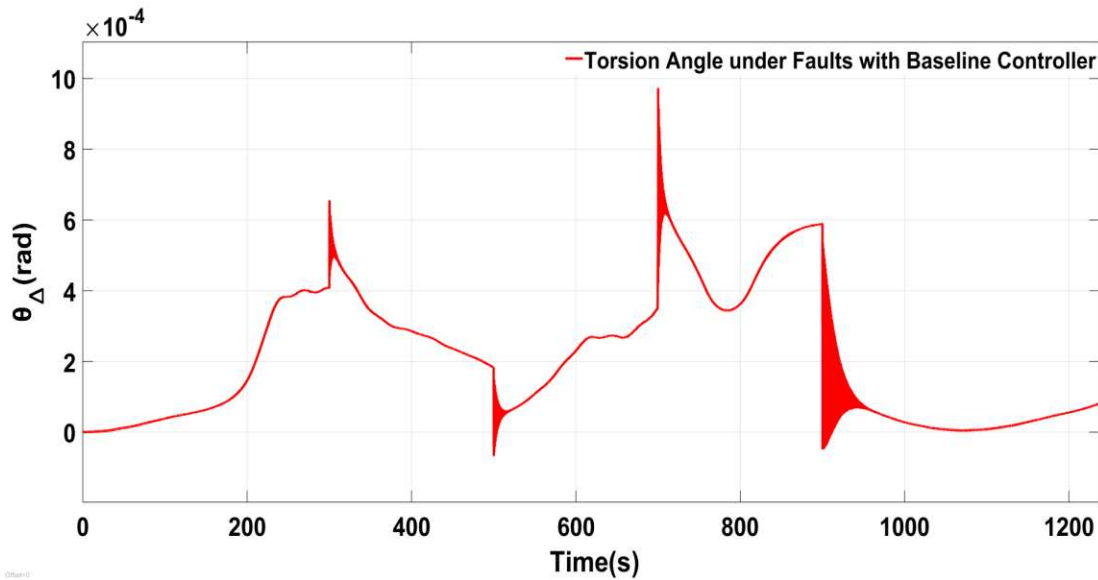


Figure 47: Effect of Case# 1 & 2 in Drive Train Torsion Angle Using Baseline Controller

5.4.3 Fault Tolerant Controller Without Faults

In this section, the adaptive fault tolerant controller performance is presented without faults. Figure 48 shows the actual power coefficient using adaptive fault tolerant controller in the fault-free case. In this case, the objective is to study the performance of the designed adaptive fault tolerant controller under no faults and how using such schemes could improve the behavior of the system. This is indicated the subsequent figures but at the cost of other parameters namely variations in the produced power and variations in the rate of change of the torsional angle of the drive train subsystem.

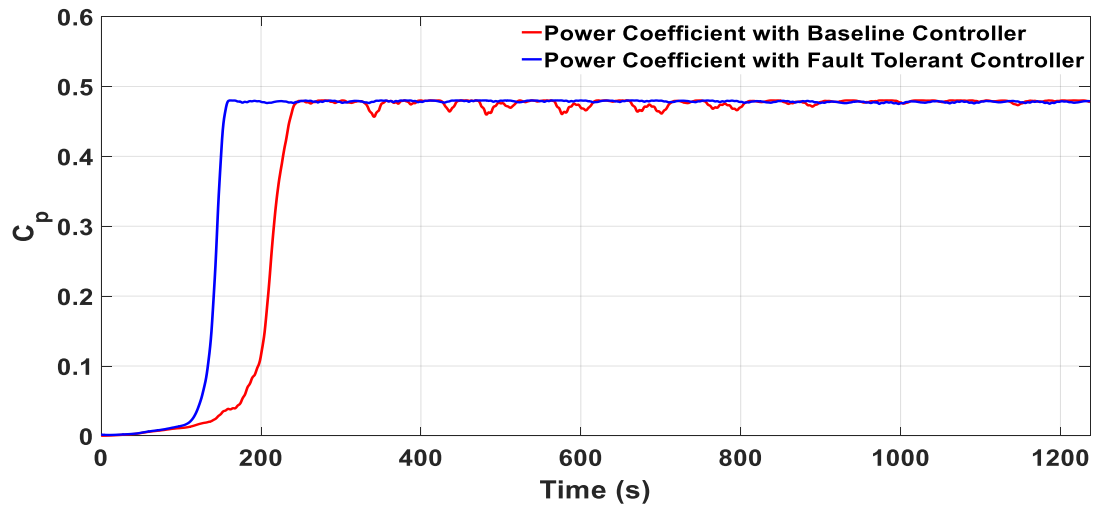


Figure 48: Power Coefficient Using AFTC Without Faults

Figure 49 shows the tip speed ratio using adaptive fault tolerant controller without faults. This gives better performance compared with baseline controller.

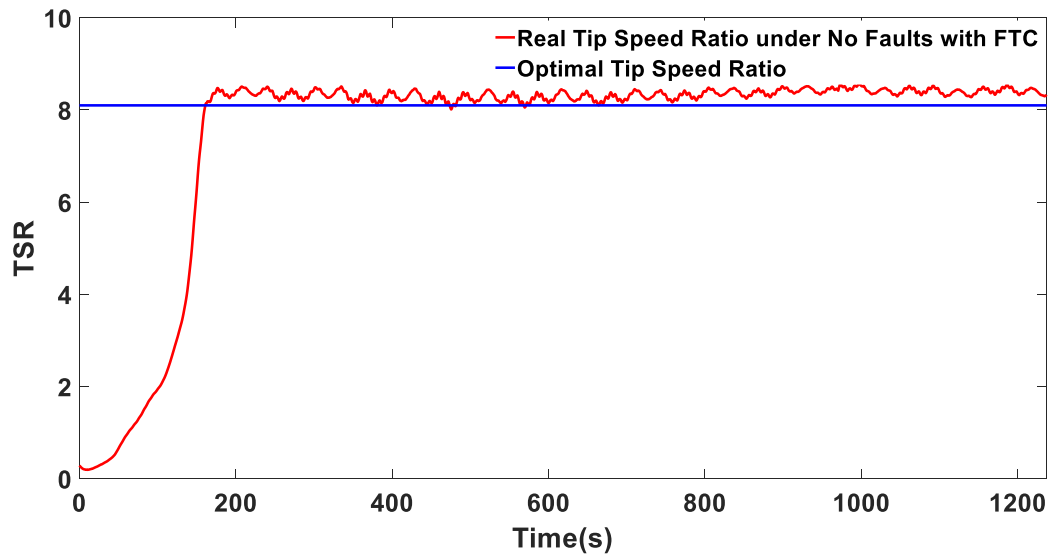


Figure 49: Tip Speed Ratio Using AFTC Without Faults

Figure 50 shows the actual power produced using adaptive fault tolerant controller without faults. This clearly indicates better performance in tracking the optimal power but with variations compared with baseline controller.

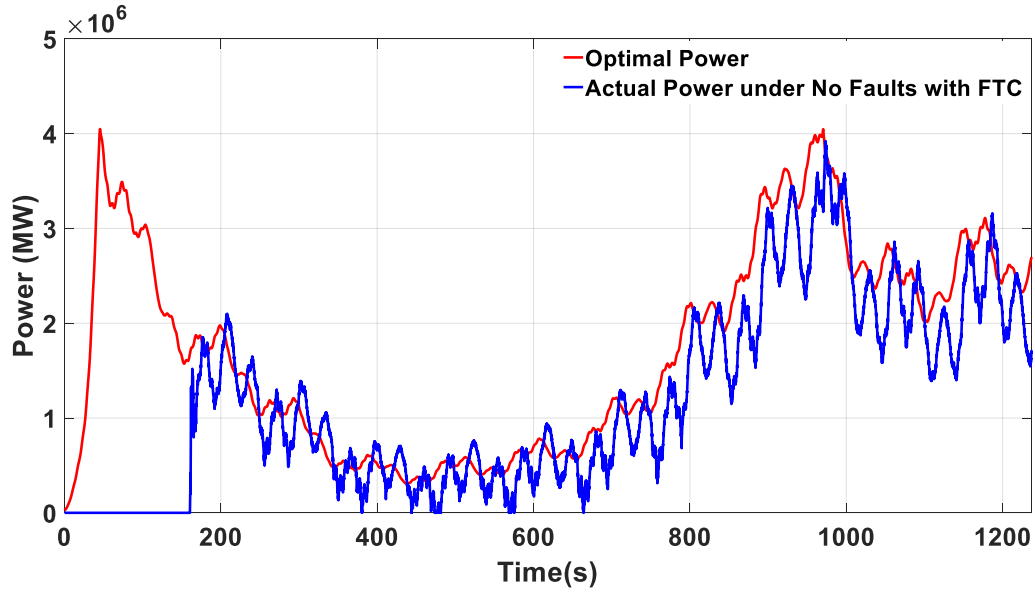


Figure 50: Actual Power Using AFTC Without Faults

Figure 51 shows the drive train torsion angle using adaptive fault tolerant control without faults. Due to close tracking of power coefficient and optimal power, the rate of change of torsional angle experienced fluctuations. Similarly, this is also indicated in the generator torque as shown in Figure 52.

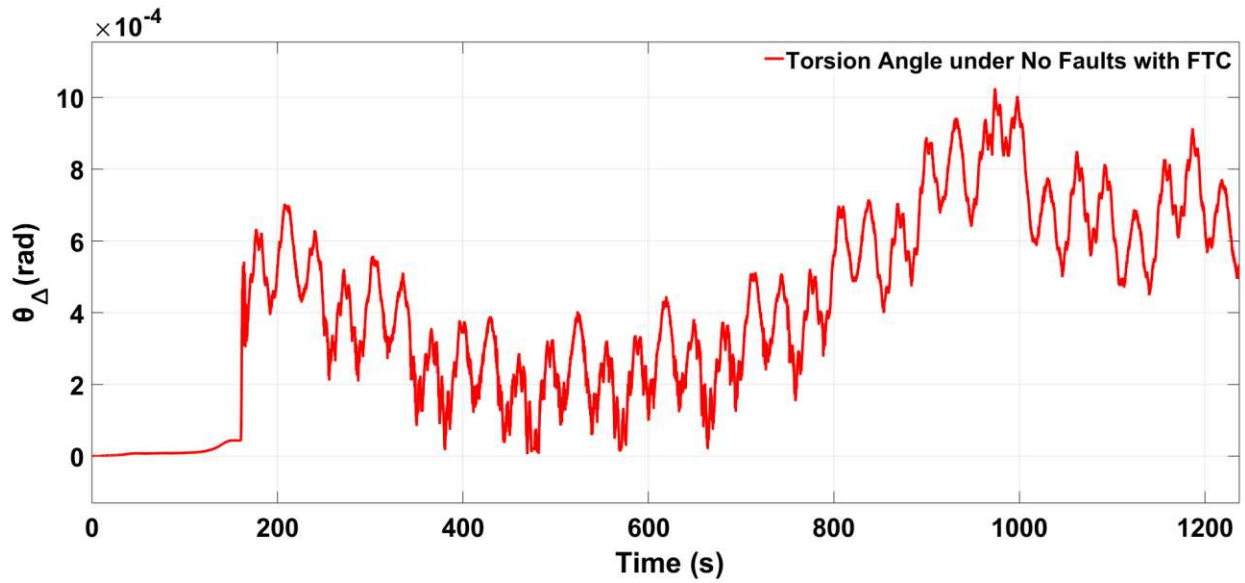
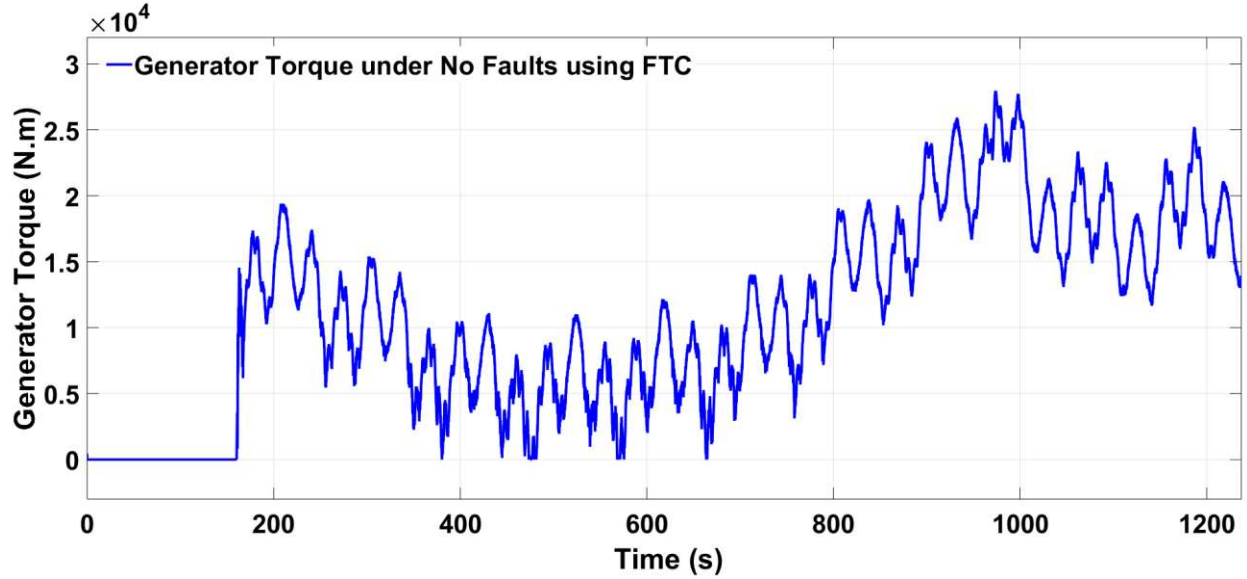


Figure 51: Drive Train Torsion Angle Using AFTC Without Faults



[Figure 52: Generator Torque Under No Faults Using AFTC]

5.4.4 Fault Tolerant Controller With Faults

To have clear effect of the fault on the system and to prove the performance of the proposed fault tolerant control scheme, the generator bias faults were doubled from fault case#1, i.e., 2000 and 5000 N.m to fault case#3, i.e., 4000 and 10,000 N.m during the same periods. This is because using the first designed faults were not having any impact on the power coefficient and this is an indication of the efficiency of the proposed adaptive fault tolerant controller in handling or accommodating the faults that occur in the torque of the generator.

As a result, the fault size is doubled to see a noticeable effect in the power production as indicated in the coming simulation figures.

Figure 53 shows fault case#3 which will be focused on the work of this thesis.

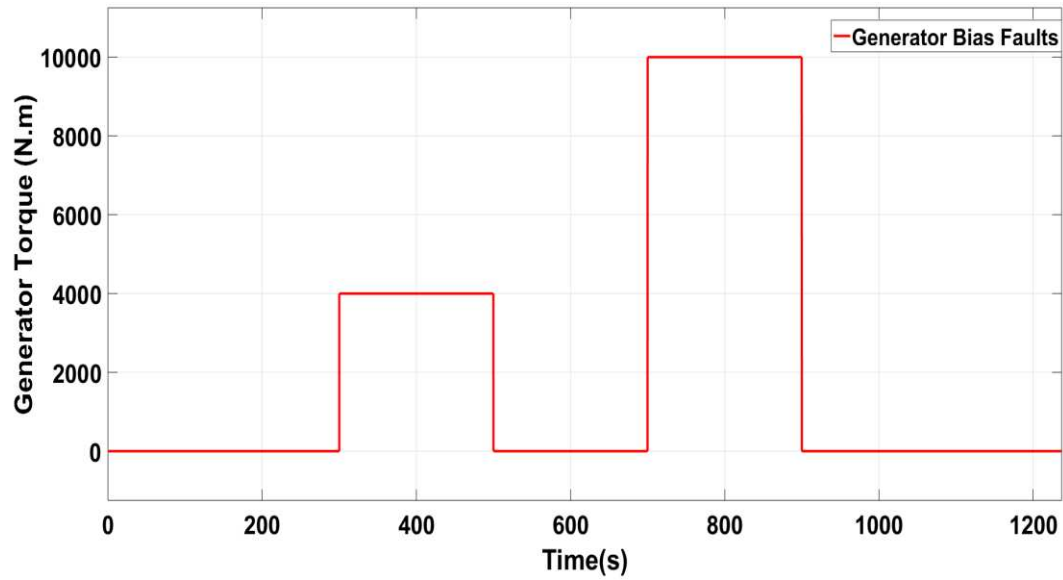


Figure 53: Fault Case # 3 in The Torque of The Generator

Figure 54 shows the effect of generator torque faults using fault case# 3 and it shows how the adaptive fault tolerant controller maintained the power coefficient despite the size of the fault magnitude.

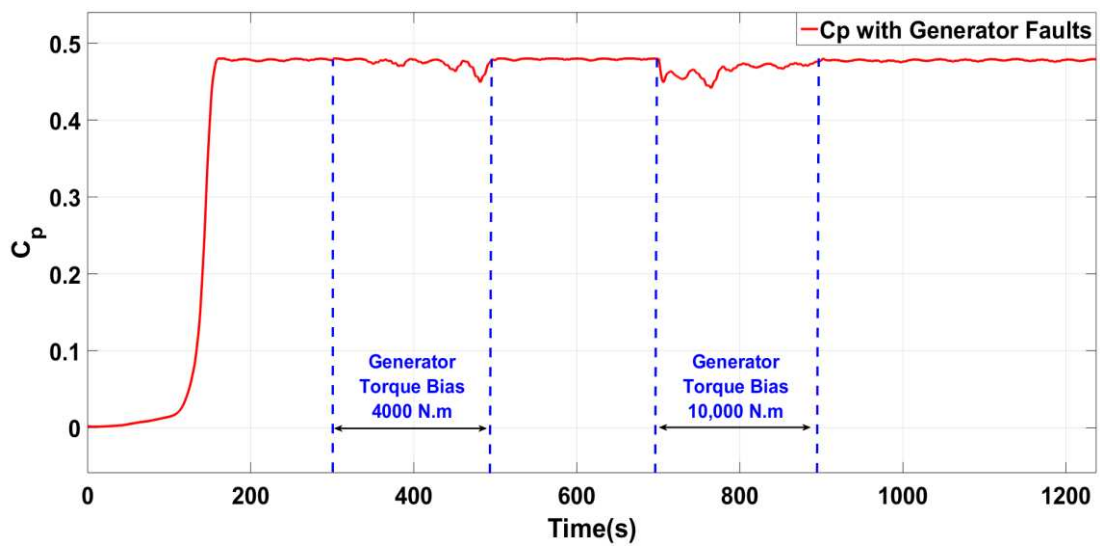


Figure 54: Effect of Fault Case# 3 on Power Coefficient Using AFTC

Figure 55 shows the effect of fault case#3 in the tip speed ratio using the adaptive fault tolerant controller. The results showed how the control scheme performed well in tracking the optimal tip speed ratio despite the large fault size compared with one simulated with baseline controller.

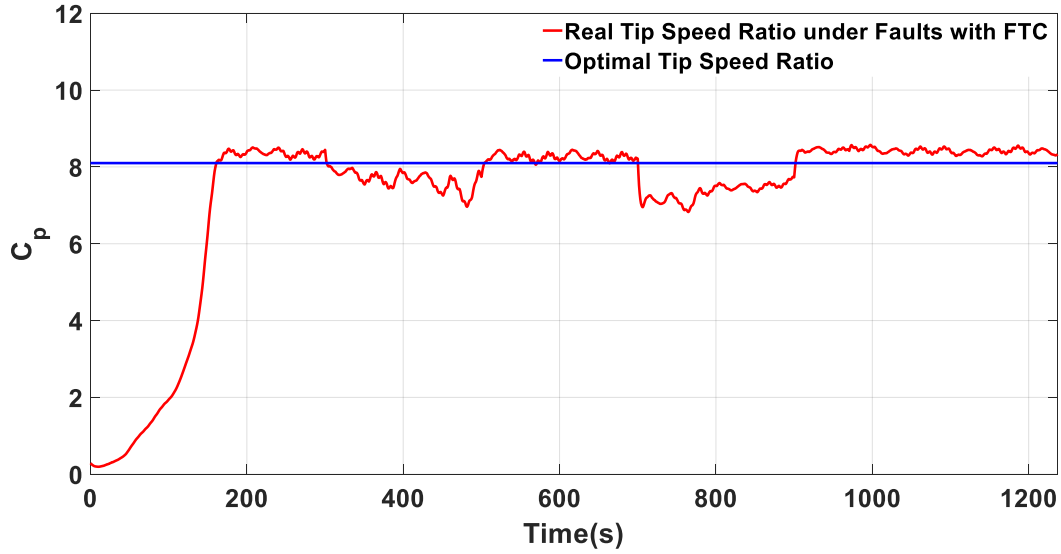


Figure 55: Effect of Fault Case# 3 on Tip Speed Ratio Using AFTC

Figure 56 shows the effect of fault case# 3 in the actual power produced using the adaptive fault tolerant controller. The results showed very promising results in tracking the optimal power despite the variations in power which is a nature of the adaptive control scheme prior to faults and also experienced high jumps at the instant of step change during faults periods.

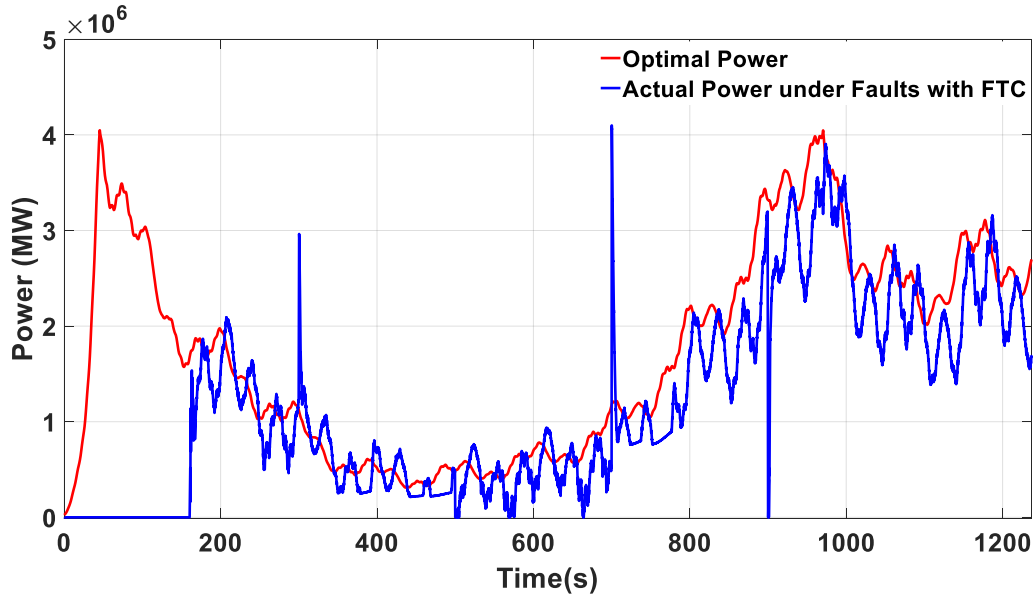


Figure 56: Effect of Fault Case# 3 on Generated Power Using AFTC

Figure 57 shows the effect of fault case# 3 on the drive train torsion angle using the adaptive fault tolerant controller. It maintained the torsional angle without sever fluctuations during faults periods except the instant step change of the faults.

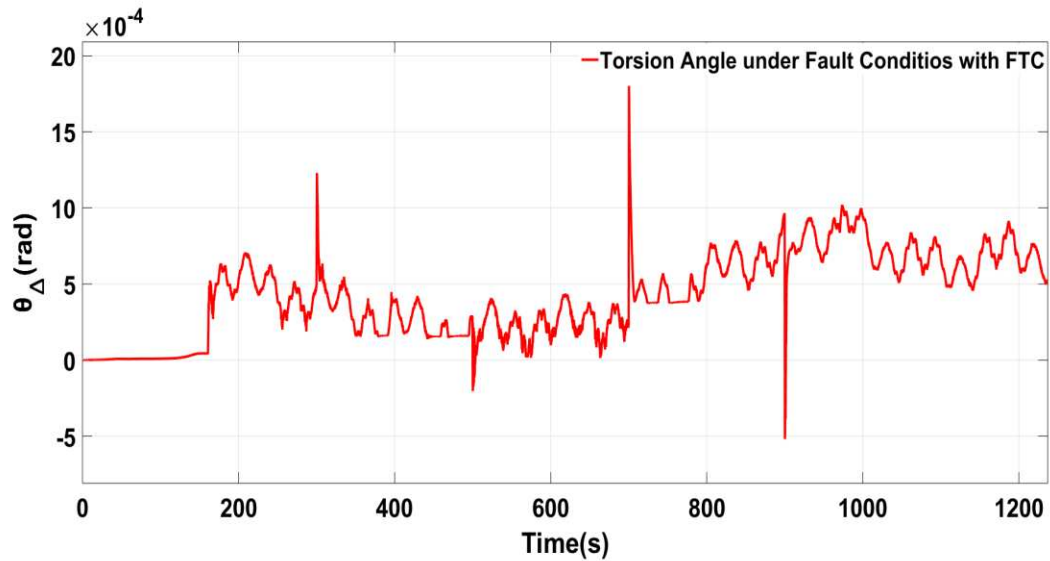


Figure 57: Effect of Generator Faults on Drive Torsion Angle Using AFTC

Figure 58 shows the effect of fault case# 3 on the generator torque using the adaptive fault tolerant controller and with similar effect on the torsional angle since it could maintain same behavior of generator torque under no fault using adaptive fault tolerant controller during faults periods except the instant step change of faults showed high jumps.

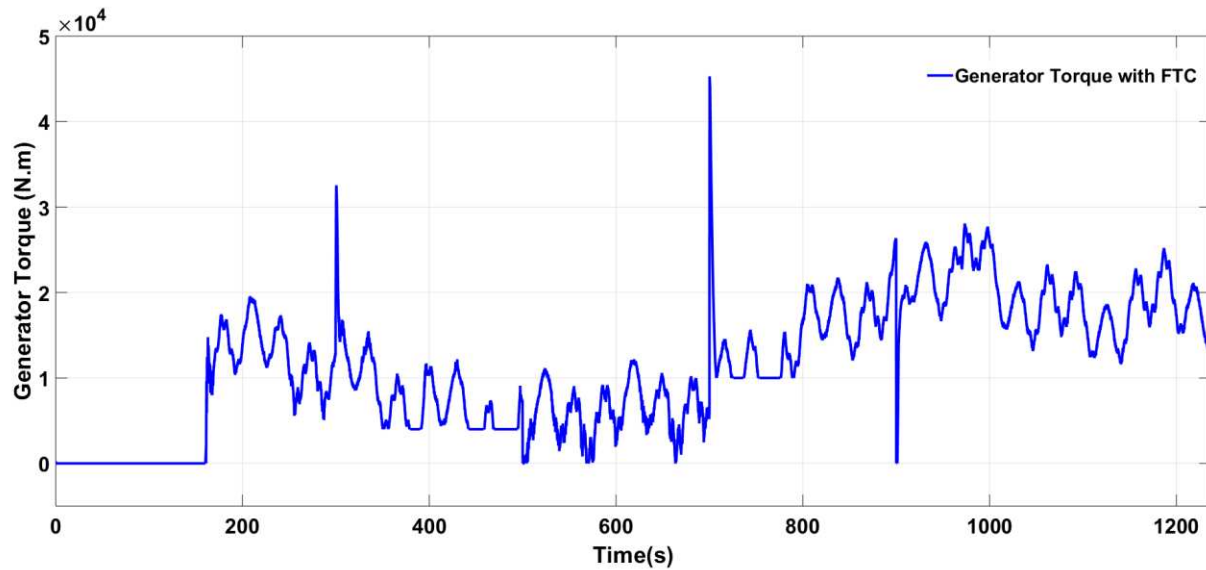


Figure 58: Effect of Generator Faults on Generator Torque using AFTC

5.4.5 Performance Criteria and Analysis

To study the performance among the different conditions for the subject system, the following performance indices are selected and detailed in Table 6.

Table 6: Performance Criteria Results

	Efficiency %	Change of Rate of Torsion Angle ($\mu.rad^2$)
Baseline Controller without Faults	65.38 %	0.6154
Baseline Controller with Faults	9.72 %	389.2
Fault Tolerant Controller without Faults	69.465 %	46.3
Fault Tolerant Controller with Faults	69.277	253.6

From performance results, it is obvious that fault tolerant could improve maintaining the control of the wind turbine at its optimal operation point at generator bias faults. In fact, using the adopted fault tolerant control improved the performance of the system without faults as its efficiency improved 65.38 % to 69.47% which indicated in figure by maintaining the power coefficient at its maximum value at 0.48. it is worth to mention that the spikes in generated power was not shown for the first case of faults, i.e. generator offset of 2000 and 5000 N.m, however, at larger faults, the power spikes appeared in the results. This proves the effectiveness of adaptive fault tolerant controller especially for first case of faults.

CHAPTER 6

Summary and Conclusion

6.1 Summary

Aerodynamic torque-based estimation techniques were implemented in two scenarios. First, aerodynamic torque was estimated directly. Second, torque coefficient was estimated then aerodynamic was calculated. Results indicated RLS-KF and RLS-NG are the best in terms of accuracy and fast convergence for the parameter estimate in both scenarios of torque coefficient estimation and aerodynamic torque estimation. However, RLS-FF showed initially great jump in estimated parameter behavior and started to converge but with large errors. Also, it could not capture the fluctuations in torque; therefore, it showed relatively poor performance compared with RLS-KF and RLS-NG. Regarding T-S fuzzy based techniques performed better than RLS-FF but still worse than RLS-KF and RLS-NG

Also, full order UIO was theoretically formulated to achieve decoupling and attenuation of disturbances by decoupling and using LMI formulation and Lyapunov theory.

Moreover, a comparative analysis was done between the baseline controller and adaptive fault tolerant controller during partial load operation of wind turbine and results showed the strong capability of adaptive fault tolerant control to optimize the power efficiency even during fault free case and to accommodate the faults while maintaining the power production of wind turbine.

6.2 Conclusion

In conclusion, wind energy is a promising renewable energy source. The idea of using fault tolerant system is significant for any critical equipment of process in order to maintain satisfactory operation even when faults occur. In this research, we studied fault estimation and tolerant control approach based on a modeled wind turbine system. A full order unknown input observer is designed and studied to simultaneously estimate the states and faults during operation of wind turbine. Also, due to the nonlinearity in model that appears in the aerodynamic torque, different estimation techniques for aerodynamic torque are studied during partial load operation of wind turbine. Moreover, a comparative analysis between baseline controller and fault tolerant controller is studied under fault-free case and fault conditions. Results showed that recursive least squares estimation based on Kalman filter and recursive least squares-based estimation using normalized gradient outperformed recursive least square estimation based on forgetting factor and Takagi-Sugeno based estimation. In addition, results showed that adaptive fault tolerant controller is capable to optimize the power efficiency during fault-free case and to accommodate the faults in the system while sustaining the power production of wind turbine.

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